Trading places

Citation for published version:
Ibikunle, G 2018, 'Trading places: Price leadership and the competition for order flow', *Journal of Empirical Finance*, vol. 49, pp. 178-200. https://doi.org/10.1016/j.jempfin.2018.09.007

Digital Object Identifier (DOI):
10.1016/j.jempfin.2018.09.007

Published In:
Journal of Empirical Finance

Trading places: price leadership and the competition for order flow

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Forthcoming in the Journal of Empirical Finance

Abstract We investigate the role of price leadership and informed trading in the competition for order flow between high-tech entrant trading venues and established national trading venues. An analysis of BATS Chi-X Europe (Chi-X), a high-tech entrant, and London Stock Exchange (LSE), an established national exchange, suggests that Chi-X's price leadership in the London market is critical to its acquisition of market share at LSE's expense. Intraday variations in price leadership, driven by informed trading, liquidity constraints and institutional trading arrangements are, however, inconsistent with the theoretical liquidity-efficiency link. Asymmetric effects of dark and algorithmic trading across the platforms are also reported.

JEL Classification: G14; G15; G18

Keywords: High-tech entrants; Price discovery; Multilateral Trading Facilities; Regulated Markets; Dark trading; Algorithmic trading

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I am grateful to the Editor (Rossen I. Valkanov), an anonymous referee, Seth Armitage, Jo Danbolt, Tobias Dieler (discussant), Alex Frino, Ben Jacobsen, Petko Kalev, Albert Menkveld, Øyvind Norli, Richard Payne, Tālis Putniņš, Chardin Wese-Simen, Damien Wallace (discussant) and colleagues at the University of Edinburgh for helpful comments and discussions. I also thank the seminar/conference participants at the UK's Financial Conduct Authority, University of Edinburgh, Macquarie University, University of Otago, Pan African University's Lagos Business School, the 2016 Annual Meetings of the European Financial Management Association, the 27th Australasian Finance and Banking Conference, the 18th Annual Conference of the Swiss Society for Financial Market Research for their comments. I thank Khaladdin Rzayev and Yuxin Sun for research assistance. The usual disclaimer applies.

"…the UK wholesale equity market is dominated by electronic computer-based trading at ultra-fast speeds. The value of information and the speed of order execution remain consistent drivers of market innovation"
U.K.'s Financial Conduct Authority (Thematic Review TR16/5)

1. Introduction

New trading venues must compete with established national platforms for market share in order to survive. Trading places in the market pecking order with established national platforms is the driving principle for most new venues. History suggests that prior to the advent of large scale electronic trading, realising this ambition in European markets proved quite impossible, as national exchanges held sway for decades with no meaningful challenges to their dominance. Established exchanges hold the advantage of being able to draw on high levels of liquidity via their existing networks, thereby reducing search costs for counterparties trading on their own platforms. According to Pagano (1989), given that search costs could be very expensive in order-driven markets, this extent of power constituted a high entry barrier to entrants. In the electronic trading age, however, search costs are rather insignificant because investors can survey a large cross section of trading venues from one location via an internet link-up. Nevertheless, not all investors have access to the technology needed to negate the impact of the search costs at the speed required to remain competitive, thus entrant venues may still struggle to attract retail investor volumes (see Foucault and Menkveld, 2008). Menkveld (2013) argues that high frequency traders (HFTs), who trade at very high speeds with computer algorithms, could play an important role in ensuring that entrant markets compete favourably with established markets. Specifically, HFTs could generate competitive quotes, which new venues require in order to succeed, making them dominant players in entrant high-tech markets.

BATS Chi-X Europe (hereinafter referred to as Chi-X) is an entrant high-tech market that has successfully challenged established European national exchanges for order flow. Monthly trading estimates from Thomson Reuters over the past five years show that Chi-X often trades places with the London Stock Exchange (LSE) as Europe's largest equity trading venue. This achievement is even more remarkable when one considers that previous entry attempts by entrant high-tech markets in Europe have largely failed; the failed EuroSETS challenge of NYSE-Euronext is an example. Generally, evidence (see as examples, O'Hara and Ye, 2011; Menkveld, 2013) indicates that entrant high-tech markets are rapidly acquiring exchange market share at the expense of established exchanges.[1] One reason for this change is the lowering of the entry barrier for new trading venues by both technological innovations and regulatory policy. Technological innovations especially are credited with the rapid lowering of the entry barrier to exchange

[1] Kwan et al. (2015) also investigate competition between incumbent exchanges and dark pools. Their study is context-driven and based on the US regulatory environment; they find that dark pools hold a competitive advantage over exchanges when trading is spread-constrained. This current paper engages with a different regulatory environment, based on the Markets in Financial Instruments Directive (MiFID) currently in force in Europe.

trading. Therefore, most entrant markets are high-tech enclaves where algorithmic trading (AT), i.e. trading with computer algorithms, thrive. AT on these new platforms manifests itself largely through the deployment of high frequency trading (HFT) strategies, hence a substantial proportion of entrant high-tech markets' price discovery is linked to HFT activity (Menkveld, 2013). Most studies agree that HFT activities improve market quality. For example, Brogaard et al. (2014), based on an analysis of 120 NASDAQ stocks from 2008–2010, suggest that HFTs help to improve market quality. Carrion (2013) finds that HFTs are more likely to trade when there is reduced liquidity, implying that they provide liquidity during periods of liquidity constraints. Hasbrouck and Saar (2013) proxy HFT by proposing a novel measure of low latency activity, which correlates with NASDAQ-defined HFT trading. They find that HFT activity improves standard proxies of market quality such as the bid-ask spread.

In this paper, we argue that new entrants must be able to attract quotes that are comparatively more informative in order to successfully challenge established platforms for order flow. Therefore, a case study is conducted to examine the intraday comparative informational quality of quotes from Chi-X's largest/main order book, CXE, and LSE's order book, the stock exchange electronic trading system (SETS). Thereafter, the determinants of the distribution of intraday price discovery are investigated and the influence of the quality of Chi-X quotes on its share in the London market for FTSE 100 stocks is tested. Our argument is driven by the contention that the level of information content in the orders and transactions on European entrant high-tech markets (e.g. Chi-X) is high enough to necessitate the need for market makers to protect themselves against informed trading by posting quotes with spreads that are generally wider than those of established national platforms (see Figure 1). Figure 1 shows that for FTSE 100 stocks traded simultaneously on LSE and Chi-X, spreads are consistently wider on Chi-X than on LSE. This implies that high-tech entrant markets do not necessarily offer quotes that are comparatively more competitive; instead, we postulate that they attract order flow through the provision of more efficient prices. One must question why a trader would choose to accept less favourable orders, even when they are presumably more efficient. The possible answer lies in the fee structures for the platforms under investigation. It is important to note that a venue's spread could be wider than its competitors', and its overall transaction costs could still be lower or approximate its competitors'. This arises when the execution costs are lower for the venue with the wider spreads. This is the case with the two venues examined in this paper; while Chi-X's spreads are generally wider on a per-minute basis, when the execution costs are taken into consideration, the transaction costs for the platform are similar to the costs for LSE. On LSE, the standard execution charge for equities is 0.45bps for the first £2.5bn of an order executed. On Chi-X, it costs 0.15bps to add the first €8bn of an order; however, there is a charge of 0.30bps to also remove the first €8bn of an order.

Consequently, we advance a new argument that superior trading activity and liquidity (narrower spreads) in established venues/markets do not necessarily translate into price leadership over high-tech entrant venues/markets. The theoretical/economic justification for these hypotheses is unambiguous. The majority of orders in markets are often posted by uninformed/noise/liquidity traders (see as an example, Vega, 2006); therefore, identifying efficient prices in a timely manner is critical to them avoiding adverse execution risks. Trading on a platform that offers prices reflecting the most up to date information ahead of its competition (price leadership) helps to achieve this aim. Price leadership is an important pursuit for trading venues; according to Wang and Yang (2011), it implies that a venue acquires and efficiently incorporates information into instrument prices in a timely manner. It also speaks to the quality of the venue's management and set up as well as to its liquidity.[2] These are significant considerations for attracting investors/traders. Therefore, price leadership is important in attracting the order flow and the revenue needed by a new venue in order to ensure a successful entry and survival.

INSERT FIGURE 1 ABOUT HERE

We find that entrant high-tech venues can achieve price leadership, even with comparatively lower levels of trading activity than incumbent exchanges. The results suggest that the competitiveness of an entrant high-tech trading venue is strongly linked to the efficiency of the prices (information content of quotes) it generates. On average, Chi-X is faster at impounding fundamental information about the value of FTSE 100 stocks into their prices than LSE, especially during early trading. This implies that the prices on Chi-X are comparatively more efficient than those on LSE. This ability appears linked to Chi-X simply being able to post/execute informative quotes at a faster pace than LSE; hence, the importance of informed traders to entrant high-tech markets. The information going into the quotes indeed may come from keenly observing order flow from the incumbent exchange (see Chordia et al., 2008). This is easily achievable if an entrant venue can develop the infrastructure needed to attract sophisticated traders with cross-market trading strategies and multi-venue trading operations. Endogenously, by successfully attracting liquidity traders, a platform becomes even more attractive to informed traders. Speed of execution, and anonymity, offered by high-tech entrants are also major draws for informed traders (see Barclay et al., 2003). The combination of the informed and uninformed traders occupying the same market space is especially critical to the price discovery process (see Kyle, 1985; Glosten and Milgrom, 1985). In an environment where superior information has become increasingly costly due to the 24-hr nature of the financial news cycle and the ubiquity of mobile apps providing timely updates, the ability of informed traders to take advantage of their information at a high speed is critical to their being compensated for sourcing trading-relevant information. Speed therefore becomes a critical component of price leadership for trading venues, and high-tech entrants are known to provide the infrastructures that aid high-speed trading. Hence, consistent with

[2] Liquidity is defined as the ability to trade large quantities of an instrument, relatively quickly, anonymously, and with little or no price impact (see Campbell et al., 1997).

the preponderance of the AT/HFT literature stream's findings, the prevalence of HFT activity on a platform improves its pricing efficiency. This suggests that Chi-X, which is crucially reliant on HFTs (Menkveld, 2013), can be expected to be more efficient in pricing instruments than LSE. Specifically, since HFTs enhance informational efficiency by speeding up price discovery and eliminating arbitrage opportunities (see Chaboud et al., 2014; Brogaard et al., 2014), one would expect to see a significant proportion of FTSE 100 stocks' new prices being discovered first at Chi-X.

Furthermore, since LSE continues to enjoy dominance with respect to trading volumes in LSE-listed stocks across all trading periods, Chi-X's price leadership in those stocks implies that LSE's larger trading volume is not associated with price discovery during the continuous trading periods. This apparent violation of the price discovery-trading activity link (see for example Barclay and Hendershott, 2003; Biais et al., 1999) is due to several factors. Firstly, it is related to the differences in the structures of both venues; for example, LSE is a hybrid trading venue with special order execution arrangements for institutional traders trading in its upstairs market, while no such arrangements exist on Chi-X. Other complicit factors include informed trading activity, venue liquidity and Chi-X's rising share of trading volume in the London equity market.

To our knowledge, this is the first study to investigate price leadership or the informativeness of quotes as drivers of order flow to trading platforms. However, three previous studies have addressed questions related to the price leadership or informativeness of quotes involving a high-tech trading venue/mechanism and an established trading venue. Barclay et al. (2003) examine how differences in services offered by Electronic Communication Networks (ECNs) and NASDAQ market makers influence the choice of trading venue for investors. They also evaluate the propensity for a higher level of informed trades on ECNs when compared to NASDAQ. Consistent with this current paper's findings, Barclay et al. (2003) find that ECNs attract more informed orders and that the lower tick sizes on ECNs attract uninformed traders in search of lower execution costs. Huang (2002) investigates the distribution of price discovery among a group of participants on NASDAQ, of which ECNs, Instinet, and Island are a part. Huang (2002) compares the quality of 30 Dow stocks quotes submitted to the NASDAQ national bid and ask montage by traditional market makers and ECNs in July 1998 and November 1999. The study finds that the two most liquid ECNs in the United States at that time, Instinet and Island, post highly informative quotes. Baillie et al. (2002), adopting a similar framework in relation to Yahoo's stock from March 1999, arrive at the same conclusion.[3] These related studies provide important insights into how computer-driven trading networks

[3]Another stream of literature examines the impact of ECN quotes on market quality; for example, Barclay and Hendershott (2003) employ ECN transactions and quote data in their analysis of price discovery and trading after the market close.

contribute to the quality of NASDAQ quotes. This current paper makes new contributions to the literature by linking the informativeness of quotes to the acquisition of order flow by a high-tech entrant venue.

2. Background to the study

2.1. Market Structure and Regulatory Framework

The Markets in Financial Instruments Directive (MiFID) of the European Union in 2007 has spurred the proliferation and growth of alternative high-tech trading venues to the established exchanges hitherto prevalent in the European markets, the so-called regulated markets (RMs). Such alternatives include multilateral trading platforms (MTFs), broker crossing networks (BCNs) and systematic internalisers (SIs). MTFs are multilateral systems that facilitate the buying and selling of RM-listed financial instruments by multiple third parties. Thus, while multilateral trading in securities takes place on MTFs, those securities must have been previously listed on RMs. The market share held by MTFs has grown tremendously since MiFID's inception, and nothing exemplifies this more than the fact that in the first half of 2013, Chi-X, which then only had an MTF status, was the largest equity trading venue in Europe by market share.[4] As at 13th November 2014 there were 151 MTFs listed on the CESR MiFID database managed by the European Securities and Markets Authority (ESMA), the EU financial markets regulator.

RMs and MTFs are largely limit order markets, which operate by matching orders on established rules of price, time and visibility priorities. RMs are mainly the national stock exchanges such as LSE. RMs and 'lit' MTFs regularly display and update market maker and limit order quotes on their order books; while 'dark' or dark pool MTFs do not display orders prior to execution, thus providing no pre-trade transparency (dark trades).[5] MiFID regulations provide for pre-trade publication exemptions,[6] and MTFs

[4] Prior to 20th May 2013, BATS Chi-X Europe only had a licence to operate MTFs; however, since being granted Recognised Investment Exchange (RIE) status, BATS Chi-X could now operate a listing exchange alongside its existing MTF operating business. The data employed in this paper is for a period after the transition of BATS Chi-X to RIE status. The price discovery dynamics of the BATS Chi-X order book employed in this analysis remains essentially the same from before and after the transition. Enquiries made with BATS Chi-X confirm that their current order books are still the same as when BATS Chi-X could only operate MTFs; thus, those books are still classic MTFs. Furthermore, achieving the RIE status was only expected to advance BATS Chi-X's fortunes with retail investors (see Stafford, 2013 in the *Financial Times*). As at May 2014, BATS Trading Limited was still listed on the CESR MiFID database as an MTF. However, BATS Europe Regulated Market was also listed as a regulated market.

[5] It is also noteworthy that while RMs are not known to directly operate dark pools, some are associated with them. For example, LSE Group is a majority shareholder in Turquoise, which operates a liquid European dark pool.

[6] There are four categories of orders that could be exempted from pre-trade transparency. The first category includes large orders, which can have large market impacts if published pre-execution; this is referred to as the Large-in-Scale (LIS) waiver. To qualify for a LIS, trades must be of a minimum size, which is dependent on the average daily turnover for each instrument. The minimum order size ranges from 50,000 for the least active stocks to 500,000 for the most active ones. The second waiver is the Reference Price waiver, which is commonly used by MTFs to maintain dark pools of liquidity. Both RMs and MTFs may avoid abiding with pre-trade transparency requirements if they passively match orders to a widely published reference price obtained from another market. For example, BATS Chi-X's dark pools for FTSE index stocks commonly passively match orders to LSE's posted midpoints. The third waiver deals with transactions negotiated privately away from the exchanges by counterparties. These transactions are usually non-

rely on these exemptions to operate dark pools. However, for all multilateral venues (RMs and MTFs), all trades must be posted as soon as possible after execution; this directive is aimed at improving transparency.

2.2. Institutional Background

LSE is a hybrid RM. Orders are executed on its main order book, the stock exchange electronic trading system (SETS), and via broker-dealers in its so-called upstairs market (see Armitage and Ibikunle, 2015). Broker-dealer trades must be reported within three minutes of execution. The FTSE 100 is LSE's main index and it contains the largest 100 eligible UK firms listed on the platform;[7] the index's firms account for more than 81% of total LSE firms' market value. Despite the increased competition for market share faced from the likes of Chi-X as a result of MiFID's enactment, LSE has managed to retain the largest share of trading for its listed stocks. In October 2014, the platform accounted for 45.40% and 66% trading share of the FTSE 100 and of all its other listed instruments, respectively. The economic difference between the platform's shares in the largest volume stocks and other instruments is evidence of the increasing attractiveness of Chi-X to high volume stock traders.

Chi-X was formed in 2011 through the merging of two of the three largest continental MTFs, BATS Europe and Chi-X Europe, which was founded by Instinet. The constituent MTFs within Chi-X continue to operate as MTFs with distinctive but integrated order books. Between its two order books, BXE and CXE, Chi-X held 35% of all FTSE 100 transactions volume in October 2014.

Both LSE and Chi-X commence continuous trading on their limit order books at 08:00:00hrs British Standard Time (BST) each trading day and conclude each trading session at 16:30:00hrs. Prior to the continuous trading session, LSE opens with a 10-minute opening auction session to set the reference price for the trading day; it also closes with a five-minute closing auction session to set the closing price (see Ibikunle, 2015 for a background on the LSE's auction sessions). Chi-X does not participate in these auctions; hence the dataset used consists of trading data for the hours between 08:00:00hrs and 16:30:00hrs. According to Ibikunle (2015) the price obtained in London at 08:00:00hrs reflects the information impounded into the price of instruments during LSE's opening auction.

3. Data and Price Discovery Measures

3.1. Sample Selection

standard and must be conducted on the basis of prevailing volume weighted bid-ask spread or a reference price if the instrument is not subject to continuous trading. The final exemption relates to iceberg orders, and is known as the Order Management Facility waiver. RMs and MTFs can waive pre-trade transparency for orders subject to order management facility until such time when they will be disclosed to the market. In practice, only a fraction of submitted orders is displayed, and once filled, the portion is refreshed using part of the previously non-displayed order.

[7] See http://www.ftse.com/Indices/UK_Indices/Downloads/FTSE_UK_Index_Series_Index_Rules.pdf for index rules

Chi-X's integrated order books, BXE and CXE, have lit and separate dark sections; both the lit and dark sections are normally allowed to interact throughout the trading day. However, whether an order hits both the lit and dark sections depends on the order type. It should be emphasised that the dark pools are separate from the integrated lit sections of the order books. We obtain two sets of data from the Thomson Reuters Tick History (TRTH) v2 database. The first is for high frequency second by second quotes data for 47 of the highest volume FTSE 100 stocks trading on both LSE's SETS and Chi-X's CXE order book between 1st July 2014 and 28th November 2014 (108 trading days).[8] We also obtain intraday tick-by-tick trades and messages data, stamped to the nearest millisecond, for the same period and for both order books.

The BXE and CXE are integrated order books, the price innovation processes on both books are therefore inextricably linked. The CXE order book consistently accounts for about 75% of Chi-X's entire FTSE 100 trading volume. The implication of this is that CXE adequately represents the trading environment at Chi-X just as much as SETS does for LSE. The final sampling date in both datasets is 28th November 2014; on that date, the 47 stocks in the sample jointly account for 75.01% of the FTSE 100 index weight.

3.2. Sample Description

In order to better observe trading activity-related dynamics, the 47 stocks are exogenously split into pound volume quintiles by using average daily trading pound volume. The trading day is also exogenously divided into seven periods in order to further grasp the intraday dynamics of price discovery distribution between the two order books.[9] Panels A and B in Table 1 present the summary statistics for LSE's SETS and BATS Chi-X's CXE order books respectively. For SETS (CXE), the average daily trading value is over £2.05 billion (£736.33 million) from a daily average of about 75,111 (47,794) trades for all the 47 stocks in the sample. The total SETS (CXE) trading value for the entire period covered by this paper is about £221.36 billion (£79.52 billion). We observe that the 18 highest volume stocks on SETS account for more than 63.74% of that value; this large trading gap between highly active LSE stocks and the relatively less active ones is in line with observations from previous literature. It is also observed that the trading gap is most pronounced during the first trading hour, when the 9 highest volume stocks account for about 42.57% of the total transactions value.

The intraday trading dynamics observed for CXE are largely in line with those of SETS. One area of distinction is how average trade sizes vary from stock to stock across quintiles and between the two order

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[8] In Section 5, in order to estimate Chi-X's market acquisition as an innovation diffusion, we extend the data to 120 months covering the period April 2008 to March 2018.

[9] We experimented with an extensive range of trading windows/intervals; we find that within the seven windows presented, there are no variations in price discovery irrespective of the approach used.

books. Generally, the trade sizes on Chi-X are lower than those on LSE. The average trade size on CXE is only about 56% of that on SETS. The values vary depending on trading interval, with the disparity greatest during the first half hour of trading for the most traded stocks. The typical CXE trade size is about 47% of SETS's during the early trading, and only about 42% for the nine most traded stocks for the same period. Also, there is less variation in the average trade sizes across stocks and time for CXE than there is for LSE. Given that in the market microstructure literature, changes in trade sizes are thought to reflect changing composition of the traders/participants in a market, one may assume that the aggregate identity of CXE traders is more consistent than that of SETS.

INSERT TABLE 1 ABOUT HERE

3.3. Measures of Price Discovery

Measuring aggregate price discovery across parallel trading venues was first attempted in Hasbrouck's (1995) seminal study of NYSE-listed instruments. Hasbrouck's (1995) Information Share (IS) approach measures a market's contribution to the unobservable efficient price of an instrument, which is traded on more than one market. This approach's definition of price discovery involves capturing the variance of innovations to the common price factor across multiple venues. A separate approach is based on Gonzalo and Granger's (1995) work on cointegration econometrics; this is the Component Share (CS), which relates only to the error correction process. The process involves the decomposition of a cointegrated time series into transitory and permanent shock components by employing error correction coefficient components. The two methods are based on the vector error correction model (VECM). Baillie et al. (2002) show that both models are directly related and that the results obtained from both models mainly stem from the error correction vector in the VECM. The models usually provide qualitatively similar results if the VECM residuals are uncorrelated. However, if there is a significant level of serial correlation in the VECM residuals, the results obtained from the two methods may be different. This difference on account of residual autocorrelation is due to Hasbrouck's (1995) inclusion of contemporaneous correlation in his measure of price discovery contribution, and Gonzalo and Granger (1995) not following the same approach. In order to rectify this problem, Hasbrouck (1995) recommends using Cholesky factorisation in order to eliminate the contemporaneous correlation.[10]

However, both measures of price discovery potentially suffer from estimation bias if noise levels differ across trading venues/price series (see Yan and Zivot, 2010; Putniņš, 2013). Thus, in addition to the CS and IS price discovery measures, the information leadership share (ILS) prescribed by Putniņš (2013)

[10] The theoretical bases and empirical approaches for the two methods are well known; thus, for parsimony, they are only presented in Appendix A.

on account of Yan and Zivot's (2010) information leadership (IL) metric is also computed for both venues as follows:

$$ILS_j^{LSE} = \frac{\left| \frac{IS_j^{LSE}}{IS_j^{BCE}} \frac{CS_j^{BCE}}{CS_j^{LSE}} \right|}{\left| \frac{IS_j^{LSE}}{IS_j^{BCE}} \frac{CS_j^{BCE}}{CS_j^{LSE}} \right| + \left| \frac{IS_j^{BCE}}{IS_j^{LSE}} \frac{CS_j^{LSE}}{CS_j^{BCE}} \right|} \tag{1}$$

$$ILS_j^{BCE} = \frac{\left| \frac{IS_j^{BCE}}{IS_j^{LSE}} \frac{CS_j^{LSE}}{CS_j^{BCE}} \right|}{\left| \frac{IS_j^{LSE}}{IS_j^{BCE}} \frac{CS_j^{BCE}}{CS_j^{LSE}} \right| + \left| \frac{IS_j^{BCE}}{IS_j^{LSE}} \frac{CS_j^{LSE}}{CS_j^{BCE}} \right|} \tag{2}$$

In the above expressions, ILS_j^{LSE} and ILS_j^{BCE} correspond to the information leadership share with respect to stock *j* for LSE and Chi-X respectively. IS_j^{LSE} and IS_j^{BCE} represent the IS with respect to stock *j* for SETS and CXE respectively, while CS_j^{LSE} and CS_j^{BCE} correspond to the CS with respect to stock *j* for SETS and CXE respectively.

In constructing the time series for each venue's stock price, the mid-point of the best ask and best bid prices during each second of the trading day across the 108-day sample period is selected. The resultant pairs of price series now form the basis of the price discovery analysis conducted. This approach is consistent with existing studies (see as examples, Hasbrouck, 1995; Huang, 2002).

4. Empirical Analysis, Results and Discussion

4.1. Price Discovery

4.1.1. Distribution of price discovery

In this section, the distribution of price discovery between the LSE order book (SETS) and the BATS Chi-X order book (BXE) is discussed. The CS estimates are not reported for two of the time periods examined, nor for two stock quintiles each in two other time periods. This is because of insufficient numbers of statistically significant error correction coefficients. As evident in Tables 2 and 3, there is a high degree of consistency for both sets of price discovery estimates. The inferences drawn regarding which platform leads the information incorporation process by looking at both sets of results are very similar. The only exception relates to the 12:00 – 13:00hrs trading interval for Quintile 3 stocks. According to the CS estimates, LSE leads the aggregate price discovery for the period, whereas the IS estimates imply the opposite. The difference between the IS estimates is statistically significant, while that of CS is not.

INSERT TABLES 2 AND 3 ABOUT HERE

It is also important to note a high level of variation within the CS estimates when compared with the IS estimates. For example, the standard deviations for the cross-sectional CS estimates for the first 30 minutes of trading are 12.95%, 18.42% and 27.02% for Quintiles 4, 3 and 1, respectively. In contrast, the corresponding IS standard deviations are 1.34%, 1.48% and 0.82% respectively; and the highest IS standard deviation for a period is 8.57% compared with 27.02% for CS. These values imply that the CS results are being driven by a handful of stocks. However, the observed level of variation across the stocks' cross section is not unusual; Hupperets and Menkveld (2002) and Eun and Sabherwal (2003) find large variations in their analysis of Dutch and US listed stocks, respectively. Furthermore, the differences between the CS and IS estimates for these stock classes are, on balance, in line with most of the previous literature (see as examples, Korczak and Phylaktis, 2010; Su and Chong, 2007). Indeed, the higher level of variation in the CS estimates is only limited to about 17% of the trading periods examined. However, given the higher level of consistency in the IS estimates across stocks, we focus most of the initial price discovery discussion on the IS estimates as reported in Table 2.

The significant variation in the CS estimates notwithstanding, both the IS and CS measures consistently agree that most of the information incorporated into the sampled stocks occur at Chi-X ahead of LSE. This is a very surprising result considering the huge differences in the share of information attributed to the two venues and the fact that most of the trading occurs on LSE. The largest disparity in IS estimates is recorded for the first 30 minutes of trading, when BATS Chi-X accounts on average for 97.38% of the price innovation on the back of just about 23.80% of trading volume between the two venues for the period. It should be noted that there is very little variation in the estimates for all of the stocks examined. While the gaps are less for the other periods, they are surprisingly large nonetheless. All Chi-X IS estimates are significantly different from the corresponding LSE estimates at the 0.001 level. It is important to understand why Chi-X holds such a commanding lead in the race for price leadership. Subsequent sections of this paper examine these issues in detail. However, first, I examine whether the results obtained for the CS and IS estimates could have been influenced by differing noise levels in the two markets.

Table 4 presents the average ILS estimates for stocks on a per quintile basis. Since ILS is a derivate of CS and IS, unbiased ILS estimates could not be obtained for similar periods as the CS. Consistent with the IS and CS estimates, BATS Chi-X leads the information incorporation process for most stocks across all the five quintiles during most trading intervals of the day. However, there are notable exceptions where results suggest that either LSE leads the information incorporation process at a conventional level of statistical significance, or there is no clear price leader between the two markets. Thus, the price leader between the two markets is not as clear cut once the differing levels of noise in the two markets is factored into the computation of the share of price discovery. Furthermore, if the length of the trading periods are considered, LSE ends up on many days as the price leader in London as Chi-X does; however, the stock cross section estimates for the intervals led by LSE are not statistically significant. This suggests that clear price leadership could not be established by either venue during those trading intervals.

ILS estimates suggest that for Quintiles 2 and 1 stocks, fundamental information is mostly incorporated first on LSE during the 09:00 – 10:00hrs interval. The same is the case for the highest trading stocks (Quintiles 5 and 4) during the longest trading interval in our analysis, 13:00 – 16:00hrs. The instances of deviation from the IS and CS appear to be related to noise differences at the two venues. These noise variations could have been generated on account of differences in market structure. For example, LSE is essentially a hybrid market with both an upstairs and a downstairs market, while Chi-X has no formal upstairs market structure. Although it does have an off-exchange trade reporting facility similar to LSE's upstairs, the rules governing both structures are clearly different. Secondly, differences in the identities/classes of dominant traders on both markets could lead to substantially large differences in both markets as to slightly bias IS and CS estimates. Menkveld (2013) identifies HFTs as the major drivers of trading activity on new entrant platforms like Chi-X, while large institutional traders, such as pension funds, are the usual trading activity drivers on established platforms like LSE.

INSERT TABLE 4 ABOUT HERE

Generally, the ILS estimates are consistent with the IS and CS values and thus one can retain the suggestion that Chi-X leads the information incorporation process for a substantial proportion of the UK stocks examined despite executing significantly lower transaction volumes than LSE. The strongest indication to that effect is recorded for the first half hour of trading as measured by the CS and IS estimates, and the same is also observed for the ILS estimates. The overall Chi-X ILS estimates for the first trading interval are 66.64%, 97.35%, 92.17%, 95.94% and 93.91% for Quintiles 5 to 1 stocks respectively, which is consistent with corresponding IS estimates of 96.67%, 97.63%, 96.87%, 97.35% and 98.16%. Thus, the finding that Chi-X is the early front-runner of the regular trading day is unambiguous. As observed with the IS and CS estimates, the ILS estimates also show a pattern of LSE gradually increasing its share of price discovery as the day progresses. The extent of price leadership posted by Chi-X is remarkable, especially given its inferior trading activity relative to LSE's figures. There are several reasons for this finding.

First, the percentage differences between the IS estimates for the two venues are generally large and only relatively small during the last half-hour of trading. Although the picture is less clear for the CS and ILS, the trend is nevertheless consistent. Price leadership is very critical to the business model of trading venues since it implies that a venue is well managed and is liquid enough to attract informed investors (see Wang and Yang, 2011). The shift in intraday price discovery leadership observed for the two venues suggests that both are able to attract informed investors trading FTSE 100 stocks. However, it is also possible that the investors generally are the same and they alternate trading venues in order to benefit from increased liquidity or stealth. The reason for stealth is the need of informed traders to hide their trading intentions for as long as possible in order to fully benefit from acquiring information (see as an example, Barclay and Warner, 1993). Consider the case of Chi-X's trading volumes and average trade sizes, which are well below those of LSE at every point of the trading day. Chi-X's average trade size is at its lowest at the point when its share of price discovery is at the highest for both IS and ILS (and second highest for CS) – 08:00 to 08:30hrs. This is also the period that the exchange records its largest order submission rate as a proportion of LSE's order submission rate. These factors suggest that Chi-X's price leadership is linked to its volume of small orders, which are preferred by informed traders looking to disguise their trading intentions. The increased aggression in order submission translates into higher liquidity and camouflage for the informed traders. The relative consistency in the average trade sizes on Chi-X also suggests that the identity of traders at the venue does not vary much across the day. Thus, the attainment of price leadership appears less linked to the migration of informed traders from LSE to Chi-X, but rather with increased market depth and liquidity afforded by a higher volume of orders and transactions.

It could also be argued that the SETS being a very liquid order book provides the right environment for camouflaging trading intentions, hence should perhaps be preferred more frequently by informed traders. However, the superior trading activity on LSE appears not to have resulted in price discovery leadership for the platform. This observation is consistent with the findings of Huang (2002), showing that NASDAQ market makers' contribution to price discovery is not systematically linked with market liquidity. Huang (2002) opined that this disconnect can be explained by the existence of institutional trading priority arrangements at NASDAQ. These arrangements invalidate the theoretical and demonstrated link between trading activity and price discovery (see as an example, Biais et al., 1999). A similar phenomenon is at play at LSE. This is linked to LSE operating as a hybrid market with a parallel upstairs market, from where executed institutional orders are reported to the SETS (the downstairs market). The value of orders executed in the upstairs market is non-negligible and has been shown by Armitage and Ibikunle (2015) to account for quite a substantial portion of information revealed at LSE. The informativeness of the upstairs is linked to the activities of its dealers, who obtain information regarding unexpressed liquidity requirements of institutional traders and thus facilitate order execution with the accumulated information. Since upstairs trades on LSE could be reported up to three minutes post-execution, LSE's ecosystem is likely to incorporate information regarding unexpressed liquidity into prices at a pace slower than the rival Chi-X's. Huang (2002) documents, as this paper finds in the case of Chi-X, that ECNs' (Instinet and Island) share of price discovery contribution is positively linked with trading volume. They associate this with informed traders trading on ECNs when there is sufficient liquidity to disguise their trading intentions (see also Kyle, 1985).

Also note that LSE competes most favourably for price leadership in the final half hour of trading, where the IS estimates for the quintiles range from 44.80% for Quintile 2 stocks to 46.40% for Quintile 5 stocks.[11] This strong showing by LSE again appears to be linked to an institutional trading arrangement on the platform. Institutional investors are allowed to submit volume weighted average price (VWAP) orders to broker-dealers for execution at the close – 16:30hrs – just before the commencement of the closing batch auction. Such orders only specify buy or sell quantities and are executed at the end of the trading day at the VWAP observed for the trading day. What this implies is that no new prices are discovered at the close since the VWAP is dependent on earlier price discovery processes. Ibikunle (2015) also reports that the most active trading period for institutional trades on LSE is late in the continuous trading day and around the closing call auction, which is due to the arrival of VWAP orders. Since the VWAP orders cannot contribute to price discovery, owing to the fact that they are priced based on previous trades, it is likely that orders are placed in advance of the close in order to influence the VWAP for the day. This conjecture is supported by results obtained by Ibikunle (2015), suggesting that LSE trades become increasingly informative around this period. The trading summaries in Table 1 also imply that this is a tenable assertion. The largest value per unit time of trading on LSE (£3.01 million/min) is recorded for the final half hour of the continuous trading day versus the middle of the trading day and the first half-hour on Chi-X. Furthermore, the largest average trade sizes for LSE are also recorded in the final half-hour of trading, suggesting a desperation to execute orders. Such implied desperation is usually linked to trading on some form of information. The average trade size on the platform rises by almost 13% in the final half hour from the previous hour to £34,873 and £34,943 for Quintiles 5 and 4 stocks respectively. This suggests that the trades recorded on LSE in the final half hour are very informative and that LSE is at its most informative during this period of the day, hence the improvement in the platform's contribution to price discovery. We examine this in subsequent analyses.

The consistency in Chi-X's trade sizes across the day, as shown in Panel B of Table 1, implies the presence of largely the same type of traders dominating trading across the different periods. These order sizes are always, on average, lower than those of LSE as shown in Table 1. Given the evidence in Menkveld (2013) regarding trading on Chi-X and the elevated levels of messages to trades ratio (average of 27.51 across all quintiles and 30.61 for Quintile 5), it is reasonable to assume that the dominant participants are likely to be HFTs. The increased frequency of order submission and execution during the periods when Chi-X holds the comparatively highest levels of IS/ILS leadership is in line with the hypothesis that informed traders step up their activity with the appearance of higher transaction volumes. The higher trading volumes act as camouflage for informed trading (Admati and Pfleiderer, 1988). Thus, during periods with

[11] For reasons already explained, ILS and CS estimates are not available for this period. We extrapolate that had there been CS estimates, consistent with the IS trend, the ILS estimates would also be at their largest during this period.

high transaction levels per unit of time such as the first half hour of trading, one should expect a correspondingly high level of informed trading activity.[12] In the next section, we first address the dominant question of intraday variation in informed trading activity, before investigating the determinants of price leadership in Section 5.3.

4.2. Informed Trading

In order to substantiate the hypothesis that BATS Chi-X has higher levels of informed trading activity than LSE, the level of informed trading is estimated by applying the probability of an informed trade (PIN) model of Easley et al. (1996) and Easley et al. (1997). PIN has also been employed as a proxy for priced information risk and information asymmetry in the wider financial economics literature (see for example Vega, 2006; Ellul and Pagano, 2006; Duarte et al., 2008; Chung and Li, 2003). Recently Lai et al. (2014) compute PIN measures for 30,095 firms across 47 countries over a 15-year period, and conclude that PIN is highly correlated with firm-level private information.[13] In the model, every trading interval commences with the informed traders obtaining a private signal on the value of the instrument with a probability of α. Subject to the arrival of a private signal, bad news will arrive with a probability of δ, while good news arrives with the probability of $(1 - \delta)$. The market maker determines the bid and ask prices for his inventory, with orders arriving from liquidity traders at the arrival rate ε. If there is new information to act on, informed traders also trade and their orders arrive at the rate μ. Thus, informed traders will buy if they receive a good news signal and sell if the signal is bad news. It is important to note that setting different arrival rates for uninformed buyers and sellers does not qualitatively alter estimations of the probability that an informed trade has occurred (see Easley et al., 2002).

By using the PIN model, we infer the unobservable distribution of trades between informed and uninformed traders from buys and sells volume data. Thus, typical quantities of buys and sells in an instrument are interpreted as uninformed trading activities and used in estimating ε, while unusual levels

[12] It is also expected that the first period of trading, which encompasses the first hour, will be highly informative, especially for lower volume quintile stocks. This expectation is in line with recent evidence from LSE as presented in Ibikunle (2015). Ibikunle (2015) reports that more than 50% of close-to-close price discovery occurs for all FTSE 100 stocks prior to 09:00:01hrs. While most of the price discovery (about 30% of the day's total) for the highest trading stocks occurs during the opening call auction (07:50 – 08:00hrs), a similar proportion of price discovery is recorded for lower volume stocks within the first 10 minutes of continuous trading (08:00 – 08:10hrs). Ibikunle (2015) argues that the results show the rapid pace of the incorporation of accumulated overnight information into the stock prices. The delay in the reflection of information for the lower volume stocks is linked to their routine failure to open via the opening call auction (see also Friederich and Payne, 2007). This argument is also consistent with the results obtained by Barclay and Hendershott (2003) and Jiang et al. (2012) in their analyses of price discovery after hours.

[13] We sample the number of buys and sells at one-minute frequency in order to compute PIN; buys and sells are determined using the Lee and Ready (1991) algorithm. For robustness, we also estimate (i) adverse selection costs as a proxy for informed trading by using the Huang and Stoll (1997) model and (ii) the Easley et al. (2012) VPIN metric, using a 50-bucket volume sorting and bulk volume buy/sell trade classification method; the inferences obtained from the additional analysis are qualitatively unchanged from those obtained from the PIN analysis.

are used in determining μ. Furthermore, the frequency of intervals during which 'abnormal' levels of buys and sells are recorded is used to compute the values of α and δ. These computations are done simultaneously by using maximum likelihood estimation. If we assume that the uninformed and informed trades arrivals follow a Poisson distribution, the likelihood function for the PIN model for each interval estimated can be expressed as:

$$L((B,S)\mid\theta) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!}, \tag{3}$$

where B and S respectively correspond to the total number of buys and sells for the day within a trading interval; $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the parameter vector for the structural model. Equation (3) represents a blend of distributions in which the possible trades are weighted by the probability of a day with no news $(1 - \alpha)$, a day with good news $(\alpha\,(1 - \delta))$ or a day with bad news $(\alpha\delta)$. Conditional on the assumption that this process occurs independently across days, Easley et al. (1996) and Easley et al. (1997) obtain the parameter vector estimates via maximum likelihood estimation. Therefore, the parameters for each of the trading intervals and for each stock in the sample are estimated by using maximum likelihood estimation. Following Easley et al. (1996) and Easley et al. (1997), PIN is computed as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}. \tag{4}$$

Table 5 presents the cross sectional means and standard deviations of the PIN estimates by pound volume quintile for both LSE and Chi-X. There are three main noticeable aspects of the results as presented, and all three are consistent with the preceding hypotheses on informed trading evolution across the two trading venues. Firstly, with only the exception of one trading interval (13:00 – 16:00hrs), Chi-X's overall PIN estimates are higher than those of LSE; even for the said interval, the difference is not statistically significant. The stock-level estimates also show that Chi-X's level of informed trading activity is higher for most stocks and during most trading intervals. Most of the instances where LSE's PINs are higher than the corresponding ones for Chi-X are shown to be for those stocks and intervals where the ILS measure of price leadership implies that LSE leads the information incorporation/price discovery process. This is unsurprising since informed orders are correlated with assets' fundamental values and the ILS is based on eliminating noise in order to obtain a clearer measure of which price series incorporates information about assets' fundamental values first. The overall mean PIN estimates for LSE trading periods are 0.118, 0.133, 0.126, 0.073, 0.110, 0.108 and 0.125 for the respective seven trading intervals, whereas the corresponding estimates for Chi-X are 0.162, 0.204, 0.171, 0.140, 0.162, 0.091 and 0.30. The differences between the corresponding estimates are statistically significant at the 0.01 level. The higher level of informed trading on Chi-X, which is consistent with the wider spreads (see Figure 1) on the exchange, could be explained by the activity of HFTs.

INSERT TABLE 5 ABOUT HERE

The property of HFT/AT that enhances the informativeness of trades on entrant high-tech markets is the speed of order submission, cancellation and transaction. By being able to trade at a fast pace, even on public signals, HFTs rapidly eliminate arbitrage opportunities and thus enhance price discovery (see Chaboud et al., 2014; Brogaard et al., 2014). As the measures of price discovery used are based on which platform impounds new information into the price of instruments ahead of the competition, Chi-X with a higher proportion of the typically faster traders should have the larger IS, CS and ILS estimates.

A second feature of the results in Table 5 is the noticeable rise in the PIN estimates during the final half hour of trading. For example, the average LSE PIN during the 16:00 – 16:30hrs interval for the highest volume stocks is about 287% (0.157) of the PIN estimate during the previous interval (0.055). The trend holds for the top three quintiles in the case of LSE and for all of the quintiles in the case of Chi-X. The differences between the two periods' PIN estimates are also statistically significant at the 0.01 level for all the quintiles and the full sample. This development is consistent with the hypothesis that informed trading activity is stepped up during the final half-hour of continuous trading. On LSE this trend applies to the highest volume stocks whose traders are the main users of the VWAP trading arrangement at the close of the trading day. Therefore it is unsurprising that the trend holds for the top three quintiles on LSE. This view is reinforced by the fact that the PIN estimates for the lower volume stocks (Quintiles 1 and 2), which are seldom traded via the VWAP mechanism, are lower in the final trading interval than the previous trading interval. Furthermore, LSE's average PIN for the highest volume stocks (0.157) during the final period is greater than that of Chi-X (0.112) for the same period at about 140% of the latter's estimate. Such a significant rise in informed trading could explain why LSE is able to increase its share of price discovery in the final half hour of trading.

The final key feature of the results in Table 5 relate to the PIN estimates during early trading on both platforms. The first hour of trading records high PIN estimates across all stocks trading on Chi-X, but to a lesser extent on LSE. The case of LSE is interesting because the lower volume stocks' trades appear to be more informative than those of the higher volume ones. This is consistent with Ibikunle's (2015) findings regarding the pattern of incorporation of information across the day. Since a large percentage (over 30%) of the close-to-close daily information for the highest volume stocks would have already been reflected in the uncrossing prices yielded at the end of the opening call auction, the early trades in the high volume stocks are unlikely to be as informative as those in the lower volumes ones. Overall, the expectation that there is a direct link between informed trading and intraday price discovery appears to be holding. The next section formally explores this link along with several others already discussed in Sections 6.1.

4.3. Determinants of new entrant price discovery

Thus far several lines of argument have been presented to explain the price discovery dynamics observed between Chi-X and LSE. It is imperative that these arguments be formally tested. Therefore, in this sub-section, we conduct a multivariate analysis using daily variables, which are computed from high frequency data. The empirical approach employed includes computing a series of stock-day panel estimations relating ILS to identified independent/determinant variables. Panel estimations are run for each of the five quintiles and the combined 47 stocks for each of the two trading venues – Chi-X and LSE. The panel estimations are done in two ways: (i) one-stage panel least squares regressions and fixed effects (stock and date) with panel corrected standard errors (PCSE) and (ii) a combination of the Hausman and Taylor (1981) seemingly unrelated regressions (SUR) and instrumental variables (IV) estimation with PCSE.[14] The SUR with IVs are employed specifically to tackle the likelihood of the endogeneity of dark and informed trading. However, the standard panel OLS with fixed effects results are also reported for one reason: evidence from previous papers (see as an example, Comerton-Forde and Putniņš, 2015) on the order execution approaches of traders implies that endogeneity is more of a concern when causally relating dark (and informed) trading to liquidity rather than to price discovery.[15] Given the size of stocks included in our sample, i.e. a small cross-section of up to 47 stocks relative to a large time series setting,[16] the most efficient estimation approach is to adopt a 3SLS estimation as a combination of the Hausman and Taylor (1981) seemingly unrelated regression (SUR) and IV estimation (see also Egger and Pfaffermayr, 2004). This approach generalises the 2SLS method, such that we are able to take account of the correlations between equations. Hence, we are able to estimate a system of simultaneous equations and test hypotheses about corresponding coefficients in the constituent equations. This is particularly useful for testing hypotheses about the differences in the magnitudes of the effects of variables for Chi-X and LSE. The 3SLS/SUR IV estimation is done in two ways for robustness. The first style involves running the first stage regression, obtaining predicted values for the instruments and then including the predicted values as independent

[14] Additionally, Newey-West standard errors are also obtained with virtually no differences observed across all results.
[15] This view is vindicated by the multivariate panel regression results presented for both the panel least squares and 3SLS/SUR IV estimations. The corresponding results for both estimation approaches are strikingly similar; indeed, in some cases, the values are unchanged. The main difference in the results is concerning the likelihood of obtaining statistically significant results. For the 3SLS/SUR IV estimations, we are more likely to obtain statistically significant results, although the explanatory powers of the models are virtually identical. Thus, it appears, consistent with Comerton-Forde and Putniņš (2015), that endogeneity does not significantly affect the least squares estimation results.
[16] The small cross-section and large time series setting referred to here is not absolute, but rather that T is significantly larger than N.

variables in the SUR framework. For the second approach, we directly run 3SLS regressions using the instruments – obtaining the first stage predicted values, followed by a 2SLS stage to obtain residuals for estimating the cross-equation correlation matrix and then the final 3SLS estimation stage. Irrespective of the approach taken, the results obtained remain qualitatively similar.

The panel regression estimated is of the following form:

$$ILS_{it} = \alpha + \beta_{PIN} PIN_{it} + \beta_{DARK} DARK_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{3} \varphi_k V_{kit} + \varepsilon_{it} \tag{5}$$

where ILS_{it} is the price discovery proxy, information leadership share, for stock i on day t. PIN_{it} is the proxy for informed trading for stock i on day t and $DARK_{it}$ is the log of pound volume of dark trades for stock i on day t.[17] HFT_{it} serves as a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock i on day t. V_{kit} is a set of k control variables which includes the log of pound trading volume, the share of pound trading volume and the log of effective spread.

Concerning the identification of good candidates for $DARK_{it}$, PIN_{it}, and HFT_{it}, the instruments must satisfy the condition of being correlated with the relevant variable to be instrumented and also be largely uncorrelated with ε_{it} in Equation (5) above. The IVs are selected by extending an approach first employed by Hasbrouck and Saar (2013) and subsequently employed by several others such as Buti et al. (2011) and Degryse et al. (2015). The approach involves using trading variables in other similar-sized stocks (specifically the averages) on day t as an instrument for the relevant trading variable in stock i. In this paper, an improvement on this approach is introduced in order to maximise the potential for the instruments being orthogonal to the error term. As conceded by Hasbrouck and Saar (2013), the average across stocks may be correlated with stock i but it is also as likely to be correlated with the error term in Equation (5), for example. Firstly, the averages of the trading variables across stocks in the same size quintile are employed in a panel least squares framework by regressing each of the endogenous variables on their corresponding cross-sectional stock averages and the other control variables. The residuals from these pre-first stage estimations are then collected and employed as IVs in the 3SLS/SUR IV estimations. The IVs yielded have the desirable property of being highly correlated with the endogenous variables. There should also be a lack of correlation with Equation (5)'s error term. The reason is that the common cross-sectional component in the stock averages should have been stripped off in explaining the changes in the endogenous variables, thus yielding only the stock-dependent factors not explained by the cross-sectional averages as residuals. The IVs for

[17] This variable is computed only for Chi-X, since LSE does not have a dark order book. Two other proxies are also used for dark trading: the first is the proportion of dark Chi-X trades in the stock relative to lit Chi-X trades in the stock for each day; and the second is the proportion of Chi-X's dark trades relative to the rest of the market trading the stock on each day. The results obtained from these two other variables are qualitatively similar to the ones presented in this paper.

$DARK_{it}$, PIN_{it}, and HFT_{it}, named $DARKRES_{it}$, $PINRES_{it}$, and $HFTRES_{it}$ respectively, are highly correlated with the respective endogenous variables (averages of 0.596 and 0.984 respectively, which are both higher than the 0.521 average in Hasbrouck and Saar, 2013). Given that the starting hypothesis of this paper is that pricing efficiency is the main driver of order flow shares, the share of trading volume is also instrumented as described above. The resultant IV, $SHARERES_{it}$ is highly correlated with the original endogenous variable with an average correlation coefficient of 0.88.[18] It is important to note that the process of deriving the IVs as described above is not part of the first stage regressions; the computed IV's are instead used as part of the first stage regressions. In the first stage regressions, we regress $DARK_{it}$, PIN_{it}, HFT_{it} and $SHARE_{it}$ on the set of instruments and control variables as described above, for each stock. The first-stage *F-statistics*, testing the null of weak instruments, show that our models do not suffer weak instruments issues, with only two test statistics (7.09 and 4.63) falling below the threshold of 10, which Stock et al. (2002) suggest is needed for 2SLS inferences to be reliable when instrumenting for $DARK_{it}$. None fall below the suggested threshold for both sets of IVs when instrumenting for the other supposedly endogenous variables. In addition, we conduct further tests to test for the instruments' relevance, weak instruments and the validity of the over-identifying restrictions in the IV regressions. In all the regressions, Cragg-Donald (1993) and Kleibergen-Paap LM statistics reject the nulls of weak instruments and under-identification, based on the Stock and Yogo (2005) critical values, respectively. All the p-values of the Sargan χ^2 test obtained also indicate that we cannot reject the null that the over-identifying restrictions are valid.

Tables 6 – 9 report the panel least squares and 3SLS/SUR IV estimation results for all the stock quintiles as well as for the overall sample. The estimation results are presented in panels within the same tables for both Chi-X and LSE. The results are strikingly similar across all four tables, thus strongly indicating that the effects of endogenously determined variables do not drive the panel least squares results. Based on the evidence presented, the most consistently significant determinant of price discovery share in London markets is the level of informed trading in a market. The higher the proportion of informed trades in a market, the higher its share of price discovery. However, the effect of informed trading on price discovery share appears to be higher for LSE; indeed LSE coefficients are usually, on average, more than twice the size of the Chi-X estimates. For example, the Chi-X estimates for the full sample are 2.07, 2.06, 2.01 and 1.48 for Tables 6 to 9 respectively, whereas the corresponding values for LSE are 5.29, 5.25, 5.22 and 4.11. All reported values are highly statistically significant. Thus, the estimates suggest that informed trading activity on LSE elicits a higher efficient price impact than on Chi-X.

However, in order to directly compare the coefficient estimates across the pairs of panel estimates in Tables 6 – 9, we re-estimate each full sample iteration of Equation (5), i.e. panel least squares, stock and

[18] For completeness, IVs based solely on Hasbrouck and Sarr's (2013) approach are also employed in the 3SLS/SUR IV estimations in this paper; all the results are qualitatively similar to the ones presented.

date fixed effects and IV, for both Chi-X and LSE as a set of simultaneous equations. Specifically, we generalise the OLS and IV estimations for a set of systems of simultaneous equations by using SUR for the OLS regressions and 3SLS/ SUR IV for the IV regressions. Thus, we estimate four sets of simultaneous equations with the full sample of 47 stocks. Thereafter, we test the null that the ratio of the Chi-X and LSE coefficients equals one for each pair of reported estimates. Rejecting this null hypothesis in the case of any pair of coefficients implies that the coefficient difference between the two platforms is statistically significant. The coefficient ratios (t-statistics) obtained are 0.39 (30.13), 0.39 (30.05), 0.39 (29.56) and 0.36 (28.87) for Tables 6 – 9 respectively, and all are statistically significant at 0.01 level of statistical significance.[19] Hence, we are able to reject the null that the pairs of estimates are identical.

There are two possible explanations for this result. The first is that the relatively consistent trade size on Chi-X makes it harder to spot informed trades in the Chi-X order flow than it is on LSE with relatively more discrimination in trade sizes across stocks. A possible second reason is the higher level of noise generated by the effects of algorithmic trading on Chi-X relative to LSE, given that Chi-X has a higher ratio of orders and cancellations to trades. The average (maximum) values of the HFT metric employed are 27.51 (100.19) and 23.84 (82.99) for Chi-X and LSE respectively, suggesting a higher level of algorithmic trading on Chi-X. The higher level of algorithmic trading could blunt informed trading impact, making it slightly harder to identify informed transactions since arbitrageurs have to sift through a larger volume of orders and trades. This is underscored by the HFT coefficient estimates in Tables 6 – 9 overwhelmingly showing that HFT impairs Chi-X's share of price discovery for all but the highest trading (Quintile 5) stocks. The full sample estimates are also highly statically significant in Tables 6, 7 and 9, and they are all negative. Contrarily, when the corresponding coefficient estimates are statistically significant for LSE, they are all positive. This implies that the level of algorithmic trading on Chi-X could have grown to a level that it sometimes impairs its share of price discovery, while algorithmic trading on LSE appears to spur its share of price discovery. The only exception to this view is in the case of the most active stocks, Quintile 5 stocks in the tables. This implies that, consistent with Brogaard et al. (2014) and Chaboud et al. (2014), for the highest trading stocks on Chi-X and all stocks trading on LSE, HFT/AT improves pricing efficiency. One possible reason for the asymmetric effect of HFT activity in the case of Chi-X trades is the ratio of HFT activity generated to the actual volume of trades eventually executed at the two venues. Lower ratio of trades to quotes could imply higher difficulty in identifying the information content of trade, although this does not seem to be the case for LSE.

INSERT TABLES 6, 7, 8 and 9 ABOUT HERE

[19] A tabulated set of results including all the variables in the Equation (5) is available on request.

With regards to the impact of dark trading on price discovery, evidence implies that the volume of dark trading adversely affects a venue's share of price discovery (compare with the reported negative impact on liquidity as reported by Degryse et al., 2015). However, most of the quintile-based estimates are not statistically significant. With the exception of the 3SLS/SUR IV results, where all coefficients are statistically significant, only three of the full sample estimates are statistically significant, and they are all negative. This is further evidence that dark trading does not enhance a venue's share of price discovery. There are several reasons why dark trading on an exchange could hamper price discovery potential of that exchange's quotes. The first reason is the lack of transparency in dark trading. Since only the submitter of a dark order has knowledge of its details, whatever information contained therein, no matter how small, will remain hidden until execution. In addition, when such orders fail to execute, the market will be none the wiser regarding their existence.

Secondly, increasing levels of dark trading, if it is at the expense of lit volumes, could lead to a reduction in price discovery for a platform. As shown by Comerton-Forde and Putniņš (2015), dark orders are generally less informative than lit trades (see also Zhu, 2014). Therefore, as traders increase their share of (relatively uninformed) dark trading in Chi-X's dark pool relative to the share of informed trades in Chi-X's lit market, Chi-X's share of price discovery should reduce. Evidence from financial media suggests that most of the traders now piling into Chi-X's dark order book are in fact large institutional traders (asset managers) executing largely uninformed liquidity-induced orders (see as an example, Stafford, 2015, in the *Financial Times*). As modelled by Zhu (2014), because liquidity orders are driven by idiosyncratic needs of the individual traders, they are less correlated than informed orders, which are correlated with the value of instruments. Hence, for an uninformed trader the risk associated with dark trading is lower than for informed traders, who could end up on the heavier side of the market thereby suffering non-execution or costly delays.

Thirdly, Degryse et al. (2015) argue that the negative effects of dark trading on market quality characteristics such as liquidity is consistent with a 'cream skimming' effect, with dark order books attracting mainly uninformed orders, thus increasing adverse selection costs on visible markets. This view is consistent with the generally wider spreads observed for Chi-X's lit market (see Figure 1).

There are two other findings in Tables 6, 7, 8 and 9 that should be highlighted. Consistent with our expectation and Huang (2002), LSE's share of trading volume for the full sample either has no or a negative effect on its share of price discovery, whereas there is strong evidence that Chi-X's share of price discovery is positively linked with its share of trading volume. As stated earlier, the most likely explanation for this phenomenon is the presence of institutional trading priority arrangements at LSE. These arrangements appear to invalidate the theoretically-established link between trading activity and price discovery (see as an example, Biais et al., 1999). The relevant idiosyncratic structure relates to LSE operating a hybrid market structure, where downstairs and upstairs markets exist in parallel. Although the information revealed by the upstairs market is non-negligible as found by Armitage and Ibikunle (2015), when it is related to the level of trading value it contributes to LSE total it is very low. Thus, per unit pound LSE's upstairs market reveals far lower information than most trading mechanisms.

Finally, the results consistently uphold the expectation, based on theory, that spreads are inversely related to price discovery (cf. Taylor, 2011). Since liquidity is inextricably linked to market efficiency (see Chordia et al., 2008), one should expect the price discovery share of a venue to increase with increasing liquidity. Thus, when the spreads narrow, the price discovery process should improve. Furthermore, the farther apart bid and ask quotes are, the more onerous is the task of determining an equilibrium price.

4.4. Competition for order flow: market share

The hypothesis that the informational quality of quotes is critical to the acquisition of high-tech entrant market share is formally tested by estimating Equation (6) for Chi-X only. As is the case with Equation (5), for robustness, four estimation approaches are used – panel least squares and the Hausman and Taylor (1981) 3SLS/SUR IV estimation methods.

$$Marketshare_{it} = \alpha + \beta_{ILS} ILS_{it} + \beta_{Tradesize} Tradesize_{it} + \beta_{Trades} Trades_{it} + \beta_{Volatility} Volatility_{it} + \varepsilon_{it} \qquad (6)$$

The Hausman and Taylor (1981) 3SLS/SUR IV is specifically employed in order to account for the possible endogeneity of the main variable of interest, ILS, which proxies the quality of quotes emanating from the trading process on Chi-X; i.e. we recognise that market share could also be a determinant for information leadership. The three other explanatory variables are selected in order to ensure consistency with the existing literature regarding the determinants of trading venue market share (see for example, Kwan et al., 2015). $Marketshare_{it}$ corresponds to the log of share of pound volume of stock i traded on day t on Chi-X, ILS_{it} is the log of information leadership share of Chi-X with respect to stock i on day t. $Tradesize_{it}$ is the log of average daily trade size in pounds traded on Chi-X for stock i on day t, *Trades* is the log of number of transactions executed on Chi-X with respect to stock i on day t, while $Volatility_{it}$ is the log of standard deviation of the intraday mid-point price return for stock i on day t.[20] With regards to the endogeneity of the ILS variable, the instrument employed is derived as described in the case of the three earlier instruments computed in Section 5.4.[21]

[20] We also estimate Equation (6) in first differences. The results are qualitatively similar to those presented in Table 10.

[21] The Hasbrouck and Saar (2013) IV procedure is also adopted for robustness. The results are qualitatively similar to those obtained based on the reported IV selection process. Weak instruments tests, as described in Section 5.3, are applied with similar outcomes.

INSERT TABLE 10 ABOUT HERE

Table 10 presents the results from the estimation of Equation (6). Consistent with the expectation that informational quality of quotes is an important determinant of market share, the ILS variable is highly significant in three of four estimations, the exception being the stock fixed effects OLS estimation. It should, however, be noted that stock fixed estimations yield significant ILS coefficients for the largest stocks when the stocks are split into quintiles. Thus, the internal variation across stocks over time appears to affect the overall sample estimates. Trade size and number of transactions are also significant determinants of market share. Volatility, when statistically significant, has a negative impact on Chi-X's market share; this is consistent with lit exchange estimates obtained by Kwan et al. (2015). The most important take away from this portion of the analysis is the critical relationship between the acquisition of market share and the quality of quotes. Evidences suggests that investors are quite concerned about the price discovery process and are likely to do business with the platform leading in this process. Estimates reported in Table 10 suggest that, in the case of the FTSE 100 stocks examined in this study, Chi-X attracts up to 6bp more in daily market share with every percentage increase in the proportion of price discovery it is responsible for during the day. On an average day in July 2018, the value of FTSE 100 stocks traded amounts to more than €6.86 billion. This implies that leading the price discovery process could potentially increase the value of trading traffic to Chi-X by €4.12 million on a trading day.

Admittedly, other factors, such as the liquidity of platforms, are also key considerations; however, these factors are inextricably linked to the efficiency of the price discovery process (Chordia et al., 2008). Financial markets perform two key functions: the provision of liquidity and price discovery (see O'Hara, 2003). The extent to which the price discovery process helps to incorporate all the available information into the prices of instruments is a measure of a market's efficiency (Fama, 1970). Therefore, all other key market factors only support the efficient reflection of all available information in instruments' prices.

5. Modelling the entrance of high-tech entrants as a financial innovation

Thus far, we have demonstrated how informational leadership has driven Chi-X's apparent successful challenging of LSE for market share. Results and the existing literature (see Menkveld, 2013) also suggest that the enabling of trading at a higher frequency on Chi-X's platform through the use of advanced hardware and software has contributed to this successful entry. Therefore, Chi-X can be viewed as an innovation, and its adoption, i.e. its acquisition of order flow, can be modelled using innovation diffusion models. We model the progressive acquisition of monthly market share in the London equity by Chi-X using an extension of the Bass (1969) innovation diffusion model (see also Mansfield, 1961;

Molyneux and Shamroukh, 1996).[22] Consistent with de Bondt and Ibáñez (2005), the model we estimate accounts for the expectation that, in addition to financial innovation dynamics, the acquisition of market share can be driven by the market microstructure factors controlled for in Equation (6). We therefore estimate the following model using a non-linear least squares approach, which uses an additive error term to model sampling and other relevant errors, as proposed by Srinivasan and Mason (1986) (see also Hansen et al., 2003); ILS is instrumented as outlined in Section 4:

$$\Delta MS_{it} = \left[\alpha + \beta\left(\frac{MS_{it}}{M_{it}}\right)\right].[M_{it} - MS_{it}].t \times [1 + \gamma_1 ln(ILS_{it}) + \gamma_2 ln(Tradesize_{it}) + \gamma_3 ln(Trades_{it}) + \gamma_4 ln(Volatility_{it})] + \epsilon_{it} \quad (7)$$

where MS_t is Chi-X's monthly average share of the London equity market trading value for the full sample of stocks examined.[23] M_t is the market penetration ceiling, which we specify to be 0.35, 0.50 and 1.0 across three iterations of Equation (7). α and β capture the pioneer effect, e.g. of LSE having already established itself as the platform for equity trading in London, and the speed of diffusion, respectively. The larger the value of β the faster the acquisition of market share by Chi-X. ILS_{it}, $Tradesize_{it}$, $Trades_t$ and $Volatility_{it}$ are defined as stated in Section 4 and thereafter computed for each month. For this section, we extend the sample to 120 months, covering the 10-year period between April 2008 and March 2018. Chi-X Europe was the first multilateral trading facility that launched ahead of the European Union's November 2007 Markets in Financial Instruments Directive (MiFID). As noted in Section 2, MiFID made it possible for alternative trading venues to penetrate the exchange market in Europe. The platform was founded in 2007; however, the trading data obtained from Thomson Reuters suggests that actual trading started in April 2008, hence the sampling period adopted. Finally, there is a key difference between the computation of $Tradesize_t$, $Trades_t$ and $Volatility_t$ in Equation (7) and that of Equation (6). While the variables in Equation (6) are for Chi-X only, in Equation (7), since we aim to capture the full London equity market's microstructure, we use values computed from the concatenated trading activity of the main order books in the London market. The order books are Chi-X's integrated orderbooks CXE and BXE (lit and dark) and LSE's SETS. Not all of the order books are in existence/trading at the start of the sample period; hence, for each time period we employ only the order books in existence and trading.

INSERT TABLE 11 HERE

Table 11 presents the results for the three iterations of Equation (7) as estimated. Firstly, all variables, except volatility, are also statistically significant and have positive values. The implication here is that the London equity market microstructure plays a significant role for the acquisition of market share

[22] We thank the referee for suggesting this analysis.
[23] We also compute market share as a proportion of the total number of transactions executed on Chi-X. We find that the estimated speeds of diffusion coefficients obtained are qualitatively similar to the ones reported in Table 11.

by a new entrant. Secondly, the ILS coefficient estimates are in line with those presented, when using log values of market share rather than the first differences, in Table 10. This is unsurprising, as we would expect that part of a market's draw for investors should be its ability to ensure a timely incorporation of new information into prices. Thirdly, we find that Chi-X's market acquisition potential is inversely related to trade size in the aggregate London equity market. This suggests that Chi-X is more likely to attract new investors when they favour using smaller trade sizes. This is consistent with the evidence presented in Table 1, which shows that Chi-X's average trade size is only about 56.47% of LSE's.

The diffusion rate estimates are only statistically significant when we set the market penetration ceiling at high levels of 0.5 and 1. Both estimates, at 0.75 and 0.63 for the 0.5 and 1 market penetration ceilings, indicate that Chi-X's penetration of the market has been very rapid.[24] This indication is consistent with transactions data, showing Chi-X rising quickly from averaging about 8% of the consolidated market value for FTSE 100 stocks in April 2008 to averages of around 20% by the end of the start of the second quarter of 2009. According to recent market data, Chi-X currently regularly averages about 26% of the consolidated daily value of the FTSE 100 stocks.[25]

6. Conclusion

In this paper, we investigate (1) what drives the acquisition of market share by entrant high-tech venues, (2) the intraday price discovery and informed trading dynamics between incumbent and entrant high-tech venues, and (3) the determinants of those dynamics, by examining the case of FTSE 100 stocks traded at the two largest equity trading venues in Europe. Results show that while LSE is still clearly the platform of choice for trading for most investors in FTSE 100 stocks, the superior trading volumes do not imply price leadership. The main contributions in this paper are six-fold. Firstly, this study extends the price discovery literature by explicitly measuring the share of price discovery in relation to informed trading across the trading day. The findings suggest that price discovery is intraday time-varying (cf. Taylor, 2011; Frijns et al., 2015). Results show that there are intraday variations in price leadership between LSE and Chi-X, with Chi-X's prices faster at reflecting new information for most of the trading day. The variation in price leadership is closely linked with informed trading on both platforms across the day, and informed trading on LSE is found to lead to a higher impact on efficient pricing than on Chi-X.

Secondly, evidence of an asymmetric impact of algorithmic trading between established and new trading venues is presented. Algorithmic/high frequency trading impairs price discovery in the case of lower

[24] By comparison, the annual speeds of diffusion, based on a similar extension to the Bass model, for high yield bonds in the UK documented by de Bondt and Ibáñez (2005) range from 0.21 to 0.45.

[25] See https://markets.cboe.com/europe/equities/market_share/index/all/.

volume Chi-X-traded instruments. For the highest trading stocks on Chi-X and all stocks traded on LSE, the influence of algorithmic/high frequency trading is found to be overwhelmingly positive.

Thirdly, the impact of dark trading on lit price discovery is found to be negative in the case of a high-tech entrant. This impact is linked to the higher level of liquidity risk for informed traders in dark pools; hence, informed traders gravitate towards lit venues, which leads to dark trades becoming inherently less informative than lit trades. However, as more traders migrate from an exchange's visible order book to its dark pool, the information generating capacity of the exchange diminishes, since dark trades offer no pre-trade transparency (see as an example, Comerton-Forde and Putniņš, 2015).

Fourthly, there appears to be a lack of connection between LSE's superior trading activity and its ability to lead the price discovery process across the day. Estimates show that LSE's share of trading volume is negatively linked to its share of price discovery. This phenomenon, which is consistent with the literature (see Huang, 2002), appears to be linked to the institutional trading arrangements on LSE. LSE operates a hybrid trading venue, which allows for delayed reporting of large institutional trades executed in the upstairs market, away from the downstairs SETS limit order book. The dealers responsible for executing the institutional trades away from the downstairs platform also have no obligation to post quotes, thereby making the upstairs institutional trades significantly less informative (cf. Armitage and Ibikunle, 2015).

The fifth contribution of this paper is the finding that LSE increases its share of price discovery across the trading day to close the day strongly, while still trailing Chi-X. This, again, could be linked to another aspect of the preferential institutional trading arrangements on LSE. On LSE, large institutional VWAP orders could be submitted for execution at the close. These trades only specify quantity and execute at the volume weighted average trading price for the trading day. Thus, their submission is an expression of trading intentions, which ultimately makes no contribution to price discovery. It is therefore likely that traders attempt to influence the closing price, in order to obtain favourable VWAPs, by posting either informative or distorting quotes/orders during the periods leading to the close. This view is underscored by the fact that the most active trading period on LSE is the period leading to and around the close (see also Ibikunle, 2015). Evidence however suggests that, across the trading day, there is a greater concentration of informed traders on Chi-X than on LSE. This partly explains why Chi-X favourably contests with LSE for price leadership despite the former's lower trading activity in the stocks examined.

Finally, we report that in addition to the microstructure properties driving Chi-X's acquisition of market share in the London equity market, financial innovation dynamics, captured within an innovation diffusion model, also drive Chi-X's acquisition of market share. The results, consistent with market/trading data, indicate that Chi-X's market acquisition speed has been substantial.

The evidence in this paper should be of interest to platform operators, policy makers and trading market participants. New high-tech venues are changing the landscape of instruments trading in Europe.

This paper shows that high-tech entrants can favourably compete for price leadership with established platforms by developing systems that foster comparatively faster incorporation of information into prices.

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Figure 1: Liquidity per minute for FTSE 100 stocks

Liquidity proxies per minute are computed for 47 FTSE 100 stocks trading on the London Stock Exchange and BATS Chi-X between 1st July 2014 and 28th November 2014. The Quoted spread is the difference between the prevailing ask and bid prices at the time of the last transaction at every 1 minute mark for each stock; the spreads are then averaged cross-sectionally across stocks. The Effective spread is measured as twice the absolute value of the difference between the last transaction price at every 1-minute interval and the corresponding midpoint of the prevailing ask and bid prices at the time of that transaction; the spreads are then averaged cross-sectionally across stocks. The time covered is from 08:00:00hrs- 16:30:00hrs London BST. Quintiles are computed on the basis of daily pound volume across the sample period.

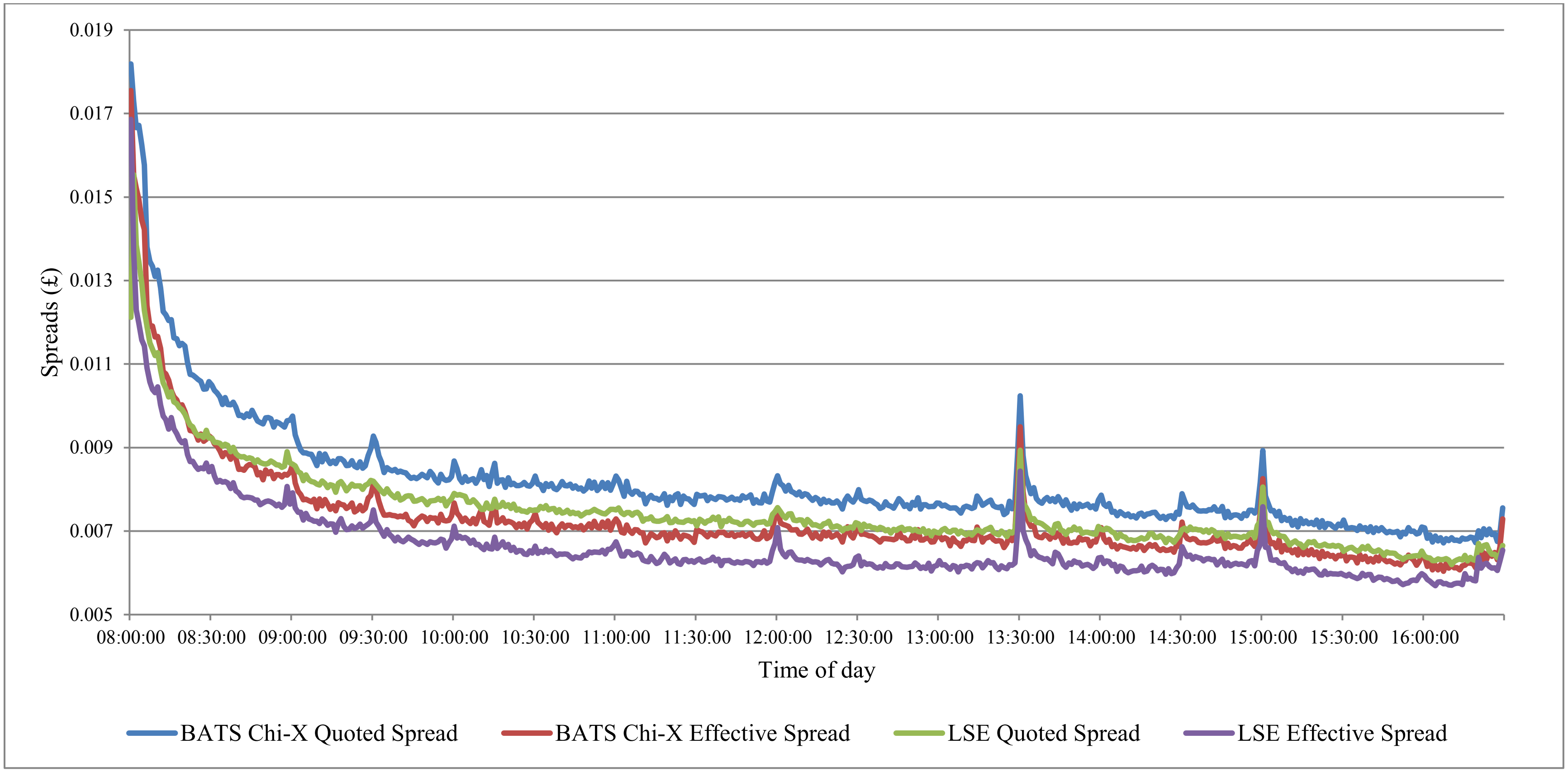

Table 1: Daily Trading summary statistics for FTSE 100 stocks

Panels A and B present daily summary statistics for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the BATS Chi-X's CXE order books respectively. The sample period covers 1st July 2014 and 28th November 2014. The quintiles are computed based on daily pound volume across the sample period.

Panel A: SETS

	Pound volume Quintile	Highest	4	3	2	Lowest	Overall
Number of Transactions	08:00 - 08:30	247.79	199.79	116.75	87.95	53.16	138.09
	08:30 - 09:00	176.48	143.69	86.44	65.99	40.72	100.57
	09:00 - 10:00	313.34	256.35	151.26	118.67	71.92	178.61
	10:00 - 12:00	536.04	426.65	257.34	196.56	122.32	301.47
	12:00 - 13:00	233.54	185.97	109.74	83.97	51.92	130.26
	13:00 - 16:00	1,084.61	831.7	480.5	360.55	228.41	584.27
	16:00 - 16:30	287.36	218.7	145.17	113.48	75.22	164.85
	All	2,879.16	2,262.86	1,347.21	1,027.17	643.66	1,598.11
Pound Volume (£'000,000)	08:00 - 08:30	8.77	5.11	3.42	1.94	1.04	3.95
	08:30 - 09:00	5.10	3.12	2.17	1.45	0.80	2.47
	09:00 - 10:00	8.73	5.6	4.01	2.61	1.42	4.37
	10:00 - 12:00	14.83	9.63	7.13	4.32	2.54	7.51
	12:00 - 13:00	6.71	4.36	2.99	1.85	1.18	3.34
	13:00 - 16:00	33.98	21.54	15.44	9	5.53	16.68
	16:00 - 16:30	10.02	7.64	4.66	2.93	1.89	5.3
	All	88.15	57.01	39.81	24.1	14.39	43.61
Average Trade Size (£'000)	08:00 - 08:30	35.41	25.59	29.28	22.01	19.54	28.58
	08:30 - 09:00	28.89	21.71	25.09	22.01	19.56	24.54
	09:00 - 10:00	27.87	21.84	26.49	21.99	19.74	24.46
	10:00 - 12:00	27.67	22.58	27.70	21.99	20.76	24.91
	12:00 - 13:00	28.75	23.44	27.22	22.03	22.64	25.61
	13:00 - 16:00	31.33	25.90	32.14	24.95	24.22	28.55
	16:00 - 16:30	34.87	34.94	32.09	25.83	25.13	32.15
	All	30.62	25.19	29.55	23.46	22.36	27.29

Panel B: CXE

	Pound volume Quintile	Highest	4	3	2	Lowest	Overall
Number of Transactions	08:00 - 08:30	142.52	102.02	51.42	37.55	26.79	70.36
	08:30 - 09:00	122.1	91.08	45.06	34.38	25.16	62.12
	09:00 - 10:00	229	167.37	84.17	66.25	47.18	116.15
	10:00 - 12:00	389.94	283.09	139.7	106.71	78.25	194.98
	12:00 - 13:00	204.87	145.43	71.81	55.68	41.95	101.6
	13:00 - 16:00	932.72	626.87	321.35	221.71	172.58	444.07
	16:00 - 16:30	53.85	43.85	19.70	12.82	11.24	27.60
	All	2,075.01	1,459.72	733.22	535.09	403.15	1,016.89
Pound Volume (£'000,000)	08:00 - 08:30	2.13	1.26	0.71	0.45	0.27	0.94
	08:30 - 09:00	1.8	1.13	0.63	0.43	0.27	0.83
	09:00 - 10:00	3.51	2.18	1.27	0.88	0.53	1.63
	10:00 - 12:00	6.07	3.84	2.19	1.45	0.93	2.82
	12:00 - 13:00	3.22	1.97	1.11	0.76	0.51	1.48
	13:00 - 16:00	16.76	9.83	5.87	3.49	2.33	7.45
	16:00 - 16:30	1.06	0.75	0.41	0.24	0.16	0.51
	All	34.55	20.97	12.2	7.7	4.99	15.67
Average Trade Size (£'000)	08:00 - 08:30	14.97	12.36	13.82	11.98	10.09	13.35
	08:30 - 09:00	14.78	12.44	14.07	12.42	10.63	13.39
	09:00 - 10:00	15.31	13.01	15.07	13.33	11.18	14.05
	10:00 - 12:00	15.56	13.58	15.66	13.54	11.84	14.47
	12:00 - 13:00	15.7	13.55	15.49	13.68	12.18	14.54
	13:00 - 16:00	17.97	15.68	18.27	15.72	13.5	16.79
	16:00 - 16:30	19.7	17.04	20.77	18.95	14.56	18.52
	All	16.65	14.36	16.63	14.38	12.39	15.41

Table 2: Information shares of FTSE 100 stocks for SETS and CXE

The table presents quintile mean information shares (IS) and standard deviations in parentheses for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the BATS Chi-X's CXE order books. The IS for both trading venues are computed per stock and for each interval on the basis of Eqs. (A.11) and (A.12). The information shares for each stock's trading periods are then cross-sectionally averaged across stocks for each period and for each quintile to obtain the IS for each quintile and for each trading period across the trading day. Wilcoxon/Mann-Whitney and Kruskal-Wallis tests are employed to test the null of no differences between the two venues' corresponding trading intervals. A venue's interval IS estimate which differs from the other venue's corresponding interval at the 0.001 level is denoted with *. † denotes the venue with the larger share of price discovery during a trading interval. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014.

	Pound volume Quintile	Highest	4	3	2	Lowest	Overall
London Stock Exchange	08:00 - 08:30	3.33* (1.73)	2.37* (1.34)	3.13* (1.48)	2.65* (1.28)	1.84* (0.82)	2.62* (1.44)
	08:30 - 09:00	38.39* (3.43)	37.43* (2.76)	36.73* (2.78)	34.71* (2.94)	36.77* (2.08)	36.76* (3.07)
	09:00 - 10:00	37.51* (2.15)	37.16* (2.07)	35.78* (3.63)	32.84* (2.47)	36.14* (1.13)	35.82* (2.93)
	10:00 - 12:00	32.78* (3.82)	29.69* (5.90)	37.64* (1.41)	26.41* (2.52)	29.56* (3.08)	29.86* (4.78)
	12:00 - 13:00	40.86* (4.09)	41.87* (2.15)	40.43* (2.77)	38.20* (4.52)	39.85* (1.39)	40.14* (3.47)
	13:00 - 16:00	25.08* (8.57)	33.37* (7.41)	22.81* (2.72)	23.83* (2.50)	24.41* (3.08)	25.77* (6.60)
	16:00 - 16:30	46.40* (0.45)	45.91* (1.19)	44.91* (1.91)	44.80* (1.11)	44.84* (1.11)	45.29* (1.44)
BATS Chi-X	08:00 - 08:30	96.67†* (1.73)	97.63†* (1.34)	96.87†* (1.48)	97.35†* (1.28)	98.16†* (0.82)	97.38†* (1.44)
	08:30 - 09:00	61.61†* (3.43)	62.57†* (2.76)	63.27†* (2.78)	65.29†* (2.94)	63.23†* (2.08)	63.24†* (3.07)
	09:00 - 10:00	62.49†* (2.15)	62.84†* (2.07)	64.22†* (3.63)	67.16†* (2.47)	63.86†* (1.13)	64.18†* (2.93)
	10:00 - 12:00	67.22†* (3.82)	70.31†* (5.90)	62.36†* (1.41)	73.59†* (2.52)	70.44†* (3.08)	70.14†* (4.78)
	12:00 - 13:00	59.14†* (4.09)	58.13†* (2.15)	59.57†* (2.77)	61.80†* (4.52)	60.15†* (1.39)	59.86†* (3.47)
	13:00 - 16:00	74.92†* (8.57)	66.63†* (7.41)	77.19†* (2.72)	76.17†* (2.50)	75.59†* (3.08)	74.23†* (6.60)
	16:00 - 16:30	53.60†* (0.45)	54.09†* (1.19)	55.09†* (1.91)	55.20†* (1.11)	55.16†* (1.11)	54.71†* (1.44)

Table 3: Component shares of FTSE 100 stocks for SETS and CXE

The table presents quintile mean component shares (CS) and standard deviations in parentheses for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the BATS Chi-X's CXE order books. CS estimates are computed for each stock and time interval by estimating the following vector error correction model (VECM):

$$\Delta P_t^{LSE} = \alpha_0^{LSE} + \alpha_1^{LSE}\hat{u}_{t-1} + \sum_{i=1}^{p}\gamma_i \Delta P_{t-i}^{LSE} + \sum_{i=1}^{p}\vartheta_i \Delta P_{t-i}^{BCE} + \varepsilon_t^{LSE},$$
$$\Delta P_t^{BCE} = \alpha_0^{BCE} + \alpha_1^{BCE}\hat{u}_{t-1} + \sum_{i=1}^{p}\gamma_i \Delta P_{t-i}^{BCE} + \sum_{i=1}^{p}\vartheta_i \Delta P_{t-i}^{LSE} + \varepsilon_t^{BCE}.$$

where P_t^{LSE} and P_t^{BCE} are observable price processes from the SETS and CXE respectively. LSE and BATS Chi-X CS estimates for each stock and within each interval are then computed:

$$CS_j^{LSE} = \frac{\alpha_1^{BCE}}{\alpha_1^{BCE} - \alpha_1^{LSE}} \quad \text{and} \quad CS_j^{BCE} = 1 - CS_j^{LSE} \text{ respectively.}$$

Adjusted Median Chi-Square tests are employed to test the null of no differences between the two venues' corresponding trading intervals. A venue's interval CS estimate which differs from the other venue's corresponding interval at 0.05 level of statistical significance is denoted with *. † denotes the venue with the larger share of price discovery during a trading interval. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014.

	Pound volume Quintile	Highest	4	3	2	Lowest	Overall
London Stock Exchange	08:00 - 08:30	4.52* (0.77)	22.73* (12.95)	30.17* (18.42)	17.89* (8.92)	32.07 (27.02)	23.60* (19.23)
	08:30 - 09:00	— —	— —	— —	— —	— —	— —
	09:00 - 10:00	46.12* (2.37)	36.80* (1.92)	40.12* (0.03)	35.41* (1.87)	43.48* (4.48)	39.51* (4.99)
	10:00 - 12:00	— —	42.55* (0.00)	— —	16.15* (0.07)	15.54* (0.77)	21.18* (10.70)
	12:00 - 13:00	— —	43.61* (6.13)	50.90† (0.40)	35.60* (6.25)	— —	42.26* (8.27)
	13:00 - 16:00	12.04* (11.23)	23.08* (4.04)	22.03* (1.20)	26.15* (7.09)	27.16* (10.20)	24.52* (9.20)
	16:00 - 16:30	— —	— —	— —	— —	— —	— —
BATS Chi-X	08:00 - 08:30	95.48†* (0.77)	77.27†* (12.95)	69.83†* (18.42)	82.11†* (8.92)	67.93† (27.02)	76.40†* (19.23)
	08:30 - 09:00	— —	— —	— —	— —	— —	— —
	09:00 - 10:00	53.88†* (2.37)	63.20†* (1.92)	59.88†* (0.03)	64.59†* (1.87)	56.52†* (4.48)	60.49†* (4.99)
	10:00 - 12:00	— —	57.45†* (0.00)	— —	83.85†* (0.07)	84.46†* (0.77)	78.82†* (10.70)
	12:00 - 13:00	— —	56.39†* (6.13)	49.10†* (0.40)	64.40†* (6.25)	— —	57.74† (8.27)

13:00 - 16:00	87.96†* (11.23)	76.92†* (4.04)	77.97†* (1.20)	73.85†* (7.09)	72.84†* (10.20)	75.48†* (9.20)
16:00 - 16:30	– –	– –	– –	– –	– –	– –

Table 4: Information leadership shares of FTSE 100 stocks for SETS and CXE

The table presents quintile mean information leadership shares (ILS) for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the BATS Chi-X's CXE order books. The ILS is computed as follows:

$$ILS_j^{LSE} = \frac{\left|\frac{IS_j^{LSE}}{IS_j^{BCE}}\frac{CS_j^{BCE}}{CS_j^{LSE}}\right|}{\left|\frac{IS_j^{LSE}}{IS_j^{BCE}}\frac{CS_j^{BCE}}{CS_j^{LSE}}\right| + \left|\frac{IS_j^{BCE}}{IS_j^{LSE}}\frac{CS_j^{LSE}}{CS_j^{BCE}}\right|} \qquad ILS_j^{BCE} = \frac{\left|\frac{IS_j^{BCE}}{IS_j^{LSE}}\frac{CS_j^{LSE}}{CS_j^{BCE}}\right|}{\left|\frac{IS_j^{LSE}}{IS_j^{BCE}}\frac{CS_j^{BCE}}{CS_j^{LSE}}\right| + \left|\frac{IS_j^{BCE}}{IS_j^{LSE}}\frac{CS_j^{LSE}}{CS_j^{BCE}}\right|}$$

where IL_j^{LSE} and IL_j^{BCE} correspond to the information leadership share with respect to stock *j* for SETS and CXE respectively. IS_j^{LSE} and IS_j^{BCE} represent the IS with respect to stock j for SETS and CXE respectively, while CS_j^{LSE} and CS_j^{BCE} correspond to the CS with respect to stock j for SETS and CXE respectively. Adjusted Median Chi-Square and Kruskal-Wallis tests are employed to test the null of no differences between the two venues' corresponding trading intervals. A venue's interval ILS estimate which differs from the other venue's corresponding interval at the 0.01 level is denoted with *. † denotes the venue that is fastest in impounding information about the fundamental value of stocks during a trading interval. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 and 28th November 2014.

	Pound volume Quintile	Highest	4	3	2	Lowest	Overall
London Stock Exchange	08:00 - 08:30	33.36 (17.80)	2.65* (3.66)	7.83* (13.70)	4.06* (7.28)	6.09* (11.26)	7.52* (13.48)
	08:30 - 09:00	–	–	–	–	–	–
	09:00 - 10:00	29.82* (0.50)	50.29† (3.40)	33.85* (0.72)	43.69* (2.52)	35.28* (7.97)	40.00* (8.42)
	10:00 - 12:00	–	8.13* (3.36)	–	75.00†* (1.43)	75.71†* (2.32)	58.63† (29.78)
	12:00 - 13:00	–	54.75†* (1.10)	26.62* (4.85)	47.29 (3.36)	–	41.64 (11.54)
	13:00 - 16:00	72.55†* (11.58)	72.42†* (16.49)	41.38* (4.74)	45.92 (16.63)	48.14 (23.86)	52.07† (21.50)
	16:00 - 16:30	–	–	–	–	–	–
BATS Chi-X	08:00 - 08:30	66.64†* (17.80)	97.35†* (3.66)	92.17†* (13.70)	95.94†* (7.28)	93.91†* (11.26)	92.48†* (13.48)
	08:30 - 09:00	–	–	–	–	–	–
	09:00 - 10:00	70.18†* (0.50)	49.71 (3.40)	66.15†* (0.72)	56.31†* (2.52)	64.72†* (7.97)	60.00†* (8.42)
	10:00 - 12:00	–	91.87†* (3.36)	–	25.00* (1.43)	24.29* (2.32)	41.37 (29.78)
	12:00 - 13:00	–	45.25* (1.10)	73.38†* (4.85)	52.71† (3.36)	–	58.36† (11.54)
	13:00 - 16:00	27.45* (11.58)	27.58* (16.49)	58.62†* (4.74)	54.08† (16.63)	51.86† (23.86)	47.93 (21.50)
	16:00 - 16:30	–	–	–	–	–	–

Table 5: Informed trading analysis

The table presents quintile mean probability of informed trading (PIN) and standard deviations in parentheses for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the BATS Chi-X's CXE order books. The PIN estimates are computed per stock and for each trading interval by using the Easley et al. (1996, 1997) PIN model. PIN parameters are computed for each stock and time interval by maximising the following likelihood function:

$$L((B,S)\,|\,\theta) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!}$$
$$+\alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!},$$

where B and S respectively correspond to the total number of buy and sell orders for the day within each trading interval. $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the parameter vector for the model. α corresponds to the probability of an information event, δ is the conditional probability of a low signal of an information event, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders. The probability that a trade is informed for each stock and within each interval is then computed as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}.$$

Wilcoxon/Mann-Whitney tests are used to test the null of no differences among the time intervals and between the two trading venues. Trading interval mean PIN estimates which differ from the immediate past interval's mean PIN at 0.01 (0.05) level for the BATS Chi-X (LSE) trading venue are denoted with *. A venue's interval PIN value which differs from the other venue's corresponding interval's PIN at the 0.05 level is denoted with †. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014.

	Pound volume Quintile	Highest	4	3	2	Lowest	Overall
London Stock Exchange	08:00 - 08:30	0.0899† (0.015)	0.0972† (0.009)	0.0983† (0.016)	0.1768† 0.0520	0.1204† (0.008)	0.1178† (0.042)
	08:30 - 09:00	0.0929† (0.018)	0.1953†* (0.028)	0.1083† (0.012)	0.1182†* (0.010)	0.1541†* (0.059)	0.1334† (0.048)
	09:00 - 10:00	0.1375* (0.028)	0.0742†* (0.013)	0.0920† (0.017)	0.1726†* (0.038)	0.0975* (0.015)	0.1142† (0.044)
	10:00 - 12:00	0.0649* (0.006)	0.0562†* (0.006)	0.0554†* (0.008)	0.0861†* (0.015)	0.0989† (0.016)	0.0726†* (0.020)
	12:00 - 13:00	0.0819* (0.027)	0.1505* (0.032)	0.1070†* (0.019)	0.1041†* (0.020)	0.1136† (0.020)	0.1104†* (0.032)
	13:00 - 16:00	0.0547†* (0.008)	0.0682* (0.010)	0.1314†* (0.013)	0.1292* (0.015)	0.1636* (0.011)	0.1077 (0.043)
	16:00 - 16:30	0.1572†* (0.027)	0.1288†* (0.033)	0.1498† (0.030)	0.0959†* (0.031)	0.0946†* (0.013)	0.1246† (0.038)
BATS Chi-X	08:00 - 08:30	0.1772† (0.049)	0.1361† (0.094)	0.1799† (0.080)	0.1577† (0.067)	0.1587† (0.063)	0.1617†* (0.073)
	08:30 - 09:00	0.1844† (0.088)	0.1448† (0.051)	0.3281†* (0.132)	0.1758† (0.080)	0.1901†* (0.106)	0.2037†* (0.114)

09:00 - 10:00	0.1525	0.1951†*	0.2609†*	0.1412†*	0.1113*	0.1706†*
	(0.036)	(0.052)	(0.093)	(0.058)	(0.055)	(0.081)
10:00 - 12:00	0.0608*	0.0861†*	0.1158†*	0.2185†*	0.2099†*	0.1398†*
	(0.033)	(0.029)	(0.044)	(0.090)	(0.069)	(0.087)
12:00 - 13:00	0.0847	0.1472*	0.2026†*	0.2266†	0.1506†*	0.1621†*
	(0.032)	(0.062)	(0.095)	(0.134)	(0.060)	(0.097)
13:00 - 16:00	0.0320†*	0.0536*	0.0766†*	0.1246*	0.1548	0.0907*
	(0.013)	(0.014)	(0.038)	(0.059)	(0.062)	(0.063)
16:00 - 16:30	0.1119†*	0.1813†*	0.2756†*	0.4119†*	0.4676†*	0.2960†*
	(0.039)	(0.036)	(0.096)	(0.068)	(0.038)	(0.148)

Table 6: Determinants of information leadership I

The table reports panel least squares regression coefficient estimates using a stock-day panel, in which the dependent variable is the log of information leadership share (ILS), for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the Chi-X's CXE order books. The estimated regressions is:

$$ILS_{it} = \alpha + \beta_{PIN} PIN_{it} + \beta_{DARK} DARK_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{3} \varphi_k V_{kit} + \varepsilon_{it}$$

where ILS_{it} is the price discovery proxy, information leadership share for stock *i* on day *t* and is as defined in Table 4. PIN_{it} is the proxy for informed trading for stock *i* on day *t* and is as defined in Table 5. $DARK_{it}$ is the log of pound volume of dark trades for stock *i* on day *t*. HFT_{it} serves as proxy for algorithmic trading and is the messages to trades ratio for stock *i* on day *t*. V_{kit} is a set of *k* control variables which include log of pound trading volume, share of trading volume and log of effective spread. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014.

	Panel A: Chi-X						Panel B: London Stock Exchange					
Pound volume Quintile	Highest	4	3	2	Lowest	Full sample	Highest	4	3	2	Lowest	Full sample
Intercept	5.57 (0.50)	30.41 (2.93***)	28.74 (2.76***)	-43.87 (-2.06**)	20.33 (4.34***)	29.90 (6.57***)	42.93 (6.75***)	32.24 (4.04***)	11.00 (1.61)	-29.76 (-1.54)	-22.99 (-1.80*)	28.44 (3.20***)
PIN	1.47 (11.1***)	3.16 (14.0***)	1.68 (16.3***)	1.58 (11.6***)	5.12 (26.7***)	2.07 (28.3***)	3.72 (17.0***)	4.23 (15.7***)	9.65 (32.5***)	4.89 (18.7***)	13.41 (38.6***)	5.29 (34.7***)
Dark	0.53 (1.09)	-0.65 (-1.20)	-0.89 (-1.63)	-0.45 (-0.66)	-0.50 (-0.90)	-0.51 (-2.38**)	–	–	–	–	–	–
HFT	0.07 (2.05**)	-0.13 (-4.7***)	-0.01 (0.42)	-0.00 (-0.08)	-0.03 (-1.02)	-0.29 (-2.10**)	-0.03 (-0.85)	0.07 (1.41)	0.04 (1.03)	0.08 (1.61)	0.06 (1.82*)	0.05 (2.34**)
Effective Spread	-0.83 (-0.68)	-0.77 (-0.64)	-2.69 (-1.97**)	-3.25 (-2.7***)	-4.41 (-3.5***)	-2.68 (-5.3***)	-5.17 (-5.6***)	-2.86 (-3.0***)	-2.18 (-2.50**)	-3.37 (-3.5***)	0.67 (0.77)	-3.42 (-7.7***)
£Volume	0.28 (0.39)	0.38 (0.94)	1.05 (1.89*)	3.83 (2.94***)	0.70 (0.62*)	0.31 (1.77*)	-1.17 (-4.4***)	-0.03 (-0.09)	0.68 (1.96**)	2.90 (3.30***)	1.54 (2.77***)	-0.04 (-0.26)
Vol. Share	0.30 (2.85***)	0.33 (3.09***)	0.23 (2.09**)	0.25 (2.20**)	0.22 (2.19**)	0.30 (6.22***)	0.17 (2.24**)	-0.05 (-0.67)	-0.04 (-0.73)	-0.10 (-1.69*)	-0.05 (-1.20)	-0.00 (-0.12)
Adj. R^2	0.21	0.31	0.26	0.23	0.50	0.25	0.33	0.33	0.61	0.41	0.67	0.39
Observations	963	963	963	963	1056	4908	963	963	963	963	1056	4908

Table 7: Determinants of information leadership II

The table reports panel least squares regression (with date fixed effects) coefficient estimates using a stock-day panel, in which the dependent variable is the log of the information leadership share (ILS), for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the Chi-X's CXE order books. The estimated regressions is:

$$ILS_{it} = \alpha + \beta_{PIN} PIN_{it} + \beta_{DARK} DARK_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{3} \varphi_k V_{kit} + \varepsilon_{it}$$

where ILS_{it} is the price discovery proxy, information leadership share for stock *i* on day *t* and is as defined in Table 4. PIN_{it} is the proxy for informed trading for stock *i* on day *t* and is as defined in Table 5. $DARK_{it}$ is the log of pound volume of dark trades for stock *i* on day *t*. HFT_{it} serves as proxy for algorithmic trading and is the messages to trades ratio for stock *i* on day *t*. V_{kit} is a set of *k* control variables which include log of pound trading volume, share of trading volume and log of effective spread. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014.

	Panel A: Chi-X						Panel B: London Stock Exchange					
Pound volume Quintile	Highest	4	3	2	Lowest	Full sample	Highest	4	3	2	Lowest	Full sample
Intercept	5.38 (0.36)	41.27 (3.34***)	41.03 (3.02***)	-3.88 (-0.13)	42.21 (2.00**)	37.88 (7.94***)	39.71 (5.54***)	44.20 (4.78***)	23.83 (2.96***)	-18.82 (-0.72)	-27.45 (-1.8*)	32.27 (9.87***)
PIN	1.44 (10.1***)	3.22 (13.7***)	1.63 (14.2***)	1.65 (11.3***)	5.10 (24.2***)	2.06 (27.9***)	3.70 (15.7***)	4.20 (14.1***)	9.62 (29.5***)	4.92 (17.2***)	13.40 (35.1***)	5.25 (34.0***)
Dark	0.34 (0.59)	-0.98 (-1.62)	-1.28 (-1.90*)	-0.43 (-0.56)	-0.15 (-0.24)	-0.75 (-3.4***)	–	–	–	–	–	–
HFT	0.07 (1.49)	-0.14 (-4.4***)	-0.01 (-0.37)	-0.02 (-0.32)	-0.03 (-0.80)	-0.05 (-3.1***)	-0.04 (-0.82)	0.08 (1.37)	0.06 (0.12)	0.01 (0.13)	0.08 (2.45**)	0.04 (1.86*)
Effective Spread	-0.31 (-0.19)	-1.76 (-1.21)	-3.02 (-1.97**)	-3.10 (-2.29**)	-4.34 (-3.2***)	-3.30 (-6.3***)	-5.44 (-5.3***)	-3.43 (-3.2***)	-3.29 (-3.4***)	-3.98 (-3.8***)	1.03 (1.10)	-3.70 (-8.2***)
£Volume	0.29 (0.73)	0.18 (0.46)	0.61 (1.01)	1.70 (0.98)	-0.74 (-0.56)	0.14 (0.81)	-1.16 (-4.0***)	-0.25 (-0.65)	0.10 (0.26)	2.43 (2.09**)	1.72 (2.64***)	-0.18 (-1.27)
Vol. Share	0.45 (3.60***)	0.30 (2.17**)	0.32 (2.36**)	0.42 (3.11***)	0.24 (2.18**)	0.32 (6.45***)	0.23 (2.52**)	-0.18 (-2.07**)	-0.06 (-1.01)	-0.07 (-0.94)	-0.06 (-1.37)	-0.02 (-0.68)
Adj. R^2	0.22	0.32	0.26	0.25	0.51	0.26	0.34	0.34	0.61	0.42	0.68	0.39
Observations	963	963	963	963	1056	4908	963	963	963	963	1056	4908

Table 8: Determinants of information leadership III

The table reports panel least squares regression (with stock fixed effects) coefficient estimates using a stock-day panel, in which the dependent variable is the log of the information leadership share (ILS), for 47 FTSE 100 stocks trading simultaneously on the London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the Chi-X's CXE order books. The estimated regressions is:

$$ILS_{it} = \alpha + \beta_{PIN} PIN_{it} + \beta_{DARK} DARK_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{3} \varphi_k V_{kit} + \varepsilon_{it}$$

where ILS_{it} is the price discovery proxy, information leadership share for stock *i* on day *t* and is as defined in Table 4. PIN_{it} is the proxy for informed trading for stock *i* on day *t* and is as defined in Table 5. $DARK_{it}$ is the log of pound volume of dark trades for stock *i* on day *t*. HFT_{it} serves as proxy for algorithmic trading and is the messages to trades ratio for stock *i* on day *t*. V_{kit} is a set of *k* control variables which include log of pound trading volume, share of trading volume and log of effective spread. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014.

	Panel A: Chi-X						Panel B: London Stock Exchange					
Pound volume Quintile	Highest	4	3	2	Lowest	Full sample	Highest	4	3	2	Lowest	Full sample
Intercept	-7.64 (-0.52)	9.77 (0.67)	8.87 (0.69)	-51.23 (-2.24**)	-1.83 (-0.10)	9.42 (1.55)	56.36 (3.46***)	23.05 (1.40)	-7.02 (-0.62)	-30.64 (-1.43)	-11.12 (-0.77)	12.45 (2.02**)
PIN	1.46 (11.0***)	3.11 (13.9***)	1.68 (16.3***)	1.51 (11.3***)	5.05 (26.1***)	2.01 (27.8***)	3.66 (16.6***)	4.19 (15.5***)	9.68 (32.4***)	4.79 (18.3***)	13.52 (39.0***)	5.22 (34.2***)
Dark	0.42 (0.51)	-0.93 (-1.22)	-2.11 (-2.9***)	-0.35 (-0.50)	-0.40 (-0.70)	-0.33 (-1.09)	–	–	–	–	–	–
HFT	0.07 (1.54)	-0.04 (-0.96)	-0.03 (-0.65)	-0.01 (-0.23)	0.02 (0.57)	0.02 (0.86)	0.04 (0.71)	0.02 (0.24)	0.07 (1.34)	0.07 (1.16)	0.01 (0.24)	0.06 (2.06**)
Effective Spread	-4.20 (-1.24)	2.47 (1.02)	0.09 (0.04)	-0.49 (-0.20)	-2.75 (-1.33)	0.26 (0.25)	-5.59 (-3.1***)	-2.05 (-1.04)	0.39 (0.26)	-1.38 (-0.69)	-3.97 (-2.7***)	-3.23 (-4.0***)
£Volume	1.91 (1.31)	1.94 (1.40)	3.80 (2.94***)	4.11 (2.96***)	1.63 (1.29)	1.47 (2.91***)	-2.16 (-2.23**)	0.47 (0.45)	1.57 (2.40**)	2.88 (3.03***)	1.33 (2.13**)	0.96 (2.67***)
Vol. Share	0.05 (0.38)	0.15 (1.28)	0.24 (1.77*)	0.02 (0.16)	0.06 (0.55)	0.05 (0.78)	0.19 (2.33**)	-0.02 (-0.22)	-0.05 (-0.86)	-0.13 (-1.99**)	-0.01 (-0.14)	0.00 (0.01)
Adj. R^2	0.23	0.32	0.26	0.23	0.51	0.27	0.34	0.33	0.61	0.42	0.68	0.40
Observations	963	963	963	963	1056	4908	963	963	963	963	1056	4908

Table 9: Determinants of information leadership IV

The table reports Hausman-Taylor 3SLS/SUR IV regression coefficient estimates using a stock-day panel, in which the dependent variable is the information leadership share (ILS), for 47 FTSE 100 stocks trading simultaneously on London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the Chi-X's CXE order books. The regression is estimated as a system of equations with the quintiles being quantiles of the full regression estimation:

$$ILS_{it} = \alpha + \beta_{PIN} PIN_{it} + \beta_{DARK} DARK_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{3} \varphi_k V_{kit} + \varepsilon_{it}$$

where ILS_{it} is the log of the price discovery proxy, information leadership share for stock *i* on day *t* and is as defined in Table 4. PIN_{it} is the proxy for informed trading for stock *i* on day *t* and is as defined in Table 5. $DARK_{it}$ is the log of pound volume of dark trades for stock *i* on day *t*. HFT_{it} serves as proxy for algorithmic trading and is the messages to trades ratio for stock *i* on day *t*. V_{kit} is a set of *k* control variables which include log of pound trading volume, share of trading volume and log of effective spread. Appropriate instrumental variables (IVs) are obtained for $DARK_{it}$ and PIN_{it} by first collecting the quintiles' cross-sectional averages of the trading variables. $DARK_{it}$ and PIN_{it} are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The residuals from this regression are each employed as IVs in the 3SLS/SUR IV estimation. The t-statistics are presented in parentheses and are derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014. Panels A and B each have only one adjusted R^2 because the quintile estimates are obtained from the quantiles of the full sample regressions.

	Panel A: Chi-X						Panel B: London Stock Exchange					
Pound volume Quintile	Highest	4	3	2	Lowest	Full sample	Highest	4	3	2	Lowest	Full sample
Intercept	4.15 (2.60***)	-0.8629 (-0.55)	-14.28 (-7.7***)	-45.24 (-26.4***)	36.49 (80.9***)	-23.52 (-13.7***)	28.34 17.45***)	-17.19 (-9.65***)	-24.81 (-13.20)	-56.92 (-30.0***)	10.94 (23.70)	26.11 (15.1***)
PIN	1.48 (22.1***)	3.16 (22.3***)	1.67 (27.8***)	1.60 (25.1***)	4.99 (71.3***)	1.48 (25.1***)	3.78 (75.60***)	4.32 (45.7***)	9.81 (62***)	4.97 (60.2***)	13.18 (69.8***)	4.11 (42.2***)
Dark	-1.21 (-7.31***)	-4.06 (-27***)	-4.48 (-31.1**)	-0.68 (-4.79***)	-0.30 (-3.90***)	-1.91 (-16.0***)	–	–	–	–	–	–
HFT	0.06 (19.6***)	-0.152 (-55***)	-0.01 (-2.10**)	0.002 (0.61)	-0.05 (-15.8***)	-0.07 (-21.7***)	0.005 (1.31)	0.11 (26.2***)	0.09 (17.6***)	0.11 (22.9***)	0.02 (4.62***)	0.12 (20.4***)
Effective Spread	-2.80 (-9.65***)	-2.06 (-8.6***)	-8.06 (-32***)	-9.27 (-39.0***)	-12.64 (-43.7***)	0.26 (1.09)	-8.48 (-32.5***)	-5.13 (-20.6**)	-15.90 (-68.2***)	-14.56 (-65.7***)	-1.09 (-3.6***)	-10.18 (-40***)
£Volume	1.81 (11.6***)	3.34 (19.7***)	5.25 (26.1***)	8.46 (43.2***)	-0.58 (-12.2***)	5.02 (28.5***)	-0.01 (-0.04)	-5.82 (33.3***)	7.10 (38.0***)	10.81 (54.2***)	1.75 (39.5***)	1.14 (6.93***)
Vol. Share	0.39 (37.7***)	0.26 (27.6***)	0.05 (4.20***)	0.26 (26.7***)	0.45 (55.2***)	0.32 (29.6***)	0.15 (19.72***)	-0.09 (-13.4***)	-0.06 (-9.75***)	-0.09 (-16.7***)	0.04 (7.73***)	-0.01 (-1.97**)

Adj. R^2						0.30						0.39
Observations	963	963	963	963	1056	4908	963	963	963	963	1056	4908
Kleibergen-Paap LM	25.27***	29.37***	27.86***	24.15***	31.60***	103.26***	3.29*	2.35	12.58***	4.392**	23.80***	12.77***
Cragg-Donald	107.98***	129.7***	202.8***	132.59***	33.60***	82.95***	24.72***	22.35***	88.08***	33.52***	110.0***	282.5***
Sargan's χ^2 p-value	0.51	0.52	0.57	0.49	0.32	0.38	0.24	0.20	0.40	0.36	0.55	0.61

Table 10: Market share and information leadership

The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is the pound volume Chi-X market share for 47 FTSE 100 stocks trading simultaneously on London Stock Exchange's Stock Exchange Electronic Trading System (SETS) and the BATS Chi-X's CXE order books. The estimated regressions is:

$$Marketshare_{it} = \alpha + \beta_{ILS} ILS_{it} + \beta_{Tradesize} Tradesize_{it} + \beta_{Trades} Trades_{it} + \beta_{Volatility} Volatility_{it} + \varepsilon_{it}$$

where $Marketshare_{it}$ corresponds to the log of share of pound volume of stock *i* traded on day *t* on Chi-X, ILS_{it} is the log of the information leadership share of Chi-X with respect to stock *i* on day *t* and is as defined in Table 4. $Tradesize_{it}$ is the log of average daily trade size in pounds traded on Chi-X for stock *i* on day *t*, $Trades_{it}$ is the log of number of transactions executed on Chi-X with respect to stock *i* on day *t*, while $Volatility_{it}$ is the log of standard deviation of the intraday mid-point price return for stock *i* on day *t*. For the Hausman-Taylor SUR IV estimation, appropriate instrumental variables (IVs) are obtained for ILS_{it} by first collecting the quintiles' cross-sectional averages of the ILS_{it}. ILS_{it} is then regressed on its corresponding cross-sectional stock averages and the other control variables for each stock. The residual from this regression is employed as an IV in the 3SLS/SUR IV estimation. The t-statistics are presented in parentheses and are derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed based on daily pound volume across the sample period 1st July 2014 to 28th November 2014. The Kleibergen-Paap LM test statistic, Cragg-Donald test statistic, and Sargan's χ^2 p-value for the IV regression presented in the final column are 85.17***, 400***, and 0.63, respectively.

Intercept	1.064 (2.42**)	1.122 (2.50**)	-1.863 (-3.66***)	-10.07 (-9.61***)
Information leadership	0.002 (6.94***)	0.002 (7.63***)	0.000 (0.29)	0.06 (4.38***)
Trade size	0.084 (5.43***)	0.082 (5.18***)	0.202 (11.26***)	2.32 (15.21***)
Transactions	0.123 (9.14***)	0.123 (9.02***)	0.207 (11.75***)	4.06 (35.48***)
Volatility	0.008 (0.71)	0.012 (1.02)	-0.05 (-3.97***)	0.007 (2.89***)
Adj. R^2	0.24	0.28	0.56	0.23
Estimation Method	OLS	OLS	OLS	Hausman- Taylor SUR IV
Fixed Effects	None	Date	Stock	None
Instrumental variables	NA	NA	NA	Yes
Observations	4908	4908	4908	4908

Table 11: Modelling market share acquisition as a diffusion of innovation

The table reports estimates for the following innovation diffusion model estimated using non-linear least square:

$$\Delta MS_{it} = \left[\alpha + \beta\left(\frac{MS_{it}}{M_{it}}\right)\right].[M_{it} - MS_{it}].t \times [1 + \gamma_1 ln(ILS_{it}) + \gamma_2 ln(Tradesize_{it}) + \gamma_3 ln(Trades_{it}) + \gamma_4 ln(Volatility_{it})] + \epsilon_{it}$$

where MS_{it} is Chi-X's monthly average share of the London equity market trading value for stock i in month t. M_{it} is the market penetration ceiling, while α and β capture the pioneer effect and the speed of diffusion respectively. ILS_{it} is the information leadership share of Chi-X with respect to stock i in month t and is as defined in Table 4. $Tradesize_{it}$ is the average daily trade size in pounds traded in London for stock i averaged across month t, $Trades_{it}$ is the number of transactions executed in London with respect to stock i in month t, while $Volatility_{it}$ is the standard deviation of the intraday mid-point price return for stock i during month t. The t-statistics are presented in parentheses. ** and *** correspond to statistical significance at 0.05 and 0.01 levels respectively. The sample period covers April 2008 to March 2018.

Market penetration ceiling	0.35	0.50	1.0
Pioneer effect	-0.45 (-7.09***)	-0.33 (-6.83***)	-0.03 (-1.52)
Speed of diffusion	0.09 (0.81)	0.75 (3.77***)	0.63 (12.84)
Information leadership	0.01 (3.05***)	0.02 (3.82***)	0.02 (4.63***)
Trade size	-0.97 (-3.02***)	-0.80 (-2.90***)	-0.78 (-1.98**)
Transactions	0.36 (2.97***)	0.64 (2.08**)	1.43 (5.4***)
Volatility	-9.76 (-1.64)	-0.92 (-1.18)	-5.71 (-0.9)
Adj. R^2	0.49	0.53	0.69
Market penetration ceiling	0.35	0.5	1
Instrumental variables	Yes	Yes	Yes
Observations	5640	5640	5640

Appendix A

1.1.Component share

There is a natural expectation that the prices of LSE-listed stocks traded on Chi-X are cointegrated with the prices of those obtained on LSE, because the underlying instruments for the cross-listed Chi-X transactions are indeed those LSE stocks. Thus, if both price series are I(1) cointegrated, $P_t = (P_{1t}, P_{2t})'$, the following VECM can be estimated:

$$\Delta P_t = \alpha\beta' P_{t-1} + \sum_{j=1}^{k} A_j \Delta P_{t-j} + e_t, \tag{A.1}$$

where α corresponds to the error correction vector, β is the cointegrating vector and e_t is a zero mean vector of serially uncorrelated innovations with covariance matrix Ω:

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}. \tag{A.2}$$

$\sigma_1^2(\sigma_2^2)$ is equal to the variance of $e_1(e_2)$ and ρ is the correlation of e_{1t} and e_{2t}. The VECM comprises of two components. The first component, $\alpha\beta' P_{t-1}$, corresponds to the long-run equilibrium dynamic between LSE and BATS Chi-X price series, while the second part, $\sum_{j=1}^{k} A_j \Delta P_{t-j}$, describes the short-term dynamics caused by pricing flaws in the market. Such imperfections include noise induced by microstructure impacts of trading large sizes.

1.2.Information share

Hasbrouck's approach begins with the transformation of Equation (A.1) into a vector moving average (VMA):

$$\Delta P_t = \psi(L) e_t, \tag{A.3}$$

which in an integrated form can be expressed as follows:

$$P_t = \iota\psi\left(\sum_{s=1}^{t} e_s\right) + \psi^*(L) e_t, \tag{A.4}$$

where $\iota = (1,1)'$ is a column vector of ones and $\psi = (\psi_1, \psi_2)$ is a row vector. $\psi^*(L)$ is a matrix of polynomials in the lag operator, L. Equation (4) is analogous to Equation (A.3). The increment ψe_t in the first portion of Equation (A.4) is deemed by Hasbrouck

(1995) as the permanent price innovation component due to new information; this component is the so-called common efficient price – the common factor. The decomposition of the variance of the common factor innovations, denoted by $\text{var}(\psi e_t) = \psi\Omega\psi'$, means that a market's information share corresponds to the part of $\text{var}(\psi e_t)$ that is due to innovations in that market. Suppose the covariance matrix *Ω* is diagonal, the information share of the *j-th* market will correspond to:

$$S_j = \frac{\psi_j^2 \sigma_j^2}{\psi\Omega\psi'}, \tag{A.5}$$

where ψ_j is the *j-th* element of ψ. Assuming that *Ω* is not diagonal, it will be impossible to systematically obtain the information share. As stated earlier, Baillie et al. (2002) show that $\frac{\psi_1}{\psi_2} = \frac{\gamma_1}{\gamma_2}$; thus, suppose the error terms are uncorrelated, the information share may be calculated using Equation 6:

$$S_j = \frac{\gamma_j^2 \sigma_j^2}{\gamma_1^2 \sigma_1^2 + \gamma_2^2 \sigma_2^2} \tag{A.6}$$

and Equation A.7:

$$\frac{S_1}{S_2} = \frac{\gamma_1^2 \sigma_1^2}{\gamma_2^2 \sigma_2^2}. \tag{A.7}$$

In a situation where the price processes are significantly correlated across markets, Equation 6 will not hold. In order to eliminate the contemporaneous correlation, Hasbrouck (1995) suggests using the Cholesky decomposition $\Omega = MM'$, where

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{pmatrix} \tag{A.8}$$

is a lower triangular matrix, resulting in the information share computed as:

$$S_j = \frac{([\psi M])^2}{\psi\Omega\psi'}, \tag{A.9}$$

where $[\psi M]_j$ is the *j-th* element of the row vector ψM. Based on Baillie et al.'s (2002) derivation, the conclusion is that:

$$\frac{S_1}{S_2} = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_2 m_{22})^2}. \tag{A.10}$$

since the information shares of both markets equal one, i.e. $S_1 + S_2 = 1$, then

$$S_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \tag{A.11}$$

and

$$S_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}. \tag{A.12}$$

One advantage of these expressions is that one can easily compute the ISs based on the covariance matrix Ω of the residual vector and the common factor coefficient vector, $\Gamma = (\gamma_1, \gamma_2)$. When the market innovations are correlated, the Cholesky factorisation is not invariant to the series ordering, and thereby levies a higher IS on the first price process. Hasbrouck (1995) suggests using different price orders and then averaging the upper and lower IS bounds to obtain a final result. Baillie et al. (2002) show that the average of the upper and lower bounds, while re-ordering the price processes for the Cholesky factorisation, yields reasonable estimates of a market's price contribution. This approach is taken to compute the IS estimates in this paper.